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What drives people to accept automated vehicles? Findings from a field experiment

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ABSTRACT

This field study aims at understanding the influence of direct experience of an automated vehicle (AV, Level 3) and explaining and predicting public acceptance of AVs through a psychological model. The model includes behavioral intention (BI) to use self-driving vehicles (SDVs, Level 5), willingness to re-ride (WTR) in our AV (Level 3), and their four potential determinants, namely perceived usefulness (PU), perceived ease of use (PEU), trust related to SDVs, and perceived safety (PS) while riding in our AV. The last two determinants are largely ignored, but we consider them critical in the context of AVs. Three-hundred students were invited as participants (passengers) to experience the AV. The trust, PU, PEU, and BI of the participants were recorded prior to their experiencing the AV; after this experience, all the constructs of the psychological model were recorded. The participants' experience with the AV was found to increase their trust, PU and PEU (but not BI), the consistency between PU/PEU and BI, and the explanatory power of BI. The model explained 55% of the variance in BI and 40% in WTR. PU, trust, and PS were found to be steady and direct predictors of both the acceptance measures; PEU predicted BI only after the participants' AV experience. Mediation analysis showed that trust also can indirectly affect AV acceptance through other determinants. Out-of-sample prediction confirmed the model's predictive capability for AV acceptance. The theoretical contributions and practical implications of the findings are discussed.

1. Introduction

According to the World Health Organization (WHO, 2015), more than 1.2 million people die from road traffic crashes each year worldwide, leading to a huge impact on health and development. More than 70% of traffic crashes were associated with human error (Dhillon, 2007). The technology of automated vehicles (AVs) has the potential to dramatically reduce the traffic crashes caused by human error (NHTSA, 2016). AVs are capable of sensing the traffic environment, navigating through software algorithm, and controlling vehicle movement without driver's decisions and actions (Xu et al., 2017). This technology is regarded as a major technological breakthrough in ensuring roadway safety. AVs also have the potential to reduce traffic congestion, increase mobility, and reduce fuel consumption (Anderson et al., 2016; Bansal et al., 2016; Fagnant and Kockelman, 2015; Howard and Dai, 2014; Litman, 2015; Liu et al., in press). According to the Society of Automotive Engineers (SAE, 2014), AVs with conditional automation (Level 3), high automation (Level 4), and full automation (Level 5) can work in "self-driving" ("automated driving") mode.

The AV technology is gaining increasing attention of vehicle manufacturers, technology companies, policymakers, and also the

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public. Several researchers and organizations forecasted long-term adoption of AVs and made different predictions (Bansal and Kockelman, 2017; Nieuwenhuijsen et al., 2018). One of the most cited studies about AV's adoption is the one by Litman (2015), who forecasted that, by 2050s, automated driving will be included as a standard feature of most new vehicles and that AVs will constitute about 40–60% of vehicle fleets, 80–100% of vehicle sales, and 50–80% of vehicle travels. Litman also predicted that AVs' beneficial impacts on increasing road safety and reducing traffic congestion are likely to appear between the 2040s and 2060s. Bansal and Kockelman (2017) predicted that self-driving vehicles (SAE Level 5) are likely to be adopted by 24.8–87.2% of vehicle fleets by 2045. For an overview of market penetration forecasting, the readers may refer to Nieuwenhuijsen et al. (2018).

As argued by Shariff et al. (2017), the biggest roadblocks standing in the path of mass adoption of AVs may be psychological, not technological. If AVs are not widely accepted by the public, neither road safety can be improved, nor the predicted benefits to society and environment be achieved (Dong et al., in press; Noy et al., 2018). Current public opinion polls and surveys reveal that the public show some resistance or a neutral attitude toward AVs (Clark et al., 2016; Haboucha et al., 2017; König and Neumayr, 2017; Smith and Anderson, 2017). To better predict, explain, and increase public acceptance of emerging technologies such as AVs, one needs to thoroughly understand what makes the public accept or reject them (Davis et al., 1989; Nordhoff et al., 2016). Recognizing the need for research into the factors shaping AV acceptance, several researchers (e.g., Abraham et al., 2017; Choi and Ji, 2015; Deb et al., 2017; Madigan et al., 2017) conducted surveys to identify the determinants of the public's intention to use AVs.

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 (Abraham et al., 2017; Madigan et al., 2017; Nordhoff et al., 2016). Second, most of the studies relied on online surveys and focused on knowing the general views of those participants who have little or no real experience of AVs (Nordhoff et al., 2017). Such an approach as this may prevent arriving at realistic findings. The participants' perceptions and responses are guided by the description of AVs provided in the questionnaire (or provided by surveyors) or other information sources (e.g., the social media) (Rahman et al., 2017). This is called 'information-exposure approach' or 'message-learning approach' in attitude research. Therefore, those participants may not be able to truly visualize the operation and functionality of the AV and the way they are likely to interact with it. As such, what they develop may only be an inaccurate mental model of AVs (Körber et al., 2018). To avoid this sort of situation, the survey must be focused on people who have the experience of riding in AVs and rely on their perspectives to understand and explain public acceptance of AVs. Recently, several field studies were carried out on automated shuttles (ASs) to elicit the opinion of the first-users of ASs (Madigan et al., 2017; Moták et al., 2017; Nordhoff et al., 2017) and understand their perceptions while riding in the AS (Salonen, 2018). In so far as the authors' knowledge goes, no such field study has been carried out so far on private AVs.

For enhancing the existing field knowledge and understanding the psychological drivers behind AV acceptance, a field experiment was conducted. For this, a number of students ($N = 300$) were invited to participate as passengers and gain first-hand experience of riding in the AV (SAE Level 3), developed by the authors. Utilizing the feedback given by those participants, we investigated the influence of the direct experience on AV acceptance and also on its psychological determinants, and built and tested a psychological model to explain and predict the participants' willingness to re-ride in the AV and intention to use self-driving vehicles (SDVs, SAE Level 5) in future.

2. Theoretical framework and hypotheses

2.1. Acceptance and psychological models to explain acceptance

Acceptance is "the precondition that will permit new automotive technologies to achieve their forecasted benefit levels" (Najm et al., 2006, p. 5-1). This definition implies that acceptance is essential for implementing new technologies in the transportation system. Adell et al. (2014) also defined driver acceptance of in-vehicle systems as "the degree to which an individual incorporates the system in his/her driving, or, if the system is not available, intends to use it" (p. 18). Although acceptance is defined in different ways, the general understanding is that it is a multi-faceted concept, involving different aspects (e.g., willingness to pay, intention to use) (Adell et al., 2014). Usually, researchers focus on the single aspect of acceptance.

Several models of human behavior and theories of technology acceptance are suggested to explain user acceptance, including the Technology Acceptance Model (TAM) (Davis, 1989; 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 UTAUT2 (Venkatesh et al., 2012). Among them, TPB was proposed to explain human behavior in general, whereas other three models were initially developed to explain technology acceptance in Information Systems research. Three types of constructs are involved in these models, including people's belief and perception of a technology, behavioral intention (BI) to use this technology, and actual usage behavior. The basic tenet of these models is that people's perceptions and beliefs (representing the information base) will determine their intentions, which, in turn, translate into actual behavior. Understanding the major perception factors that shape intention and actual behavior is critical. In TAM, perceived usefulness (PU) and perceived ease of use (PEU) are recognized as the two direct predictors of BI (which will be introduced later). TPB includes three components of BI—attitude, subjective norm, and perceived behavioral control (similar to PEU). It suggests that positive attitude, favorable normative, and volition control beliefs will positively affect BI in using a technology. In UTAUT, performance expectancy (i.e., PU), effort expectancy (i.e., PEU), and social influence are assumed to positively affect BI, which, together with facilitating conditions, positively influence actual behavior. In UTAUT2, three more constructs (hedonic motivation, price value, and habit) are added.

The above-cited models have already been used to explain driver's acceptance of new in-vehicle technologies (Park and Kim, 2014; Rahman et al., 2017). These models have also been adopted for recent survey-based studies on AVs and ASs (Choi and Ji, 2015;

Lee et al., 2017; Moták et al., 2017) and field studies on ASs (Madigan et al., 2017; Moták et al., 2017; Nordhoff et al., 2017), to explain people's intention to use AVs and ASs. These studies share certain findings, one among them being the confirmation of the capability of these psychological models in accounting for BI. They also produced incongruent or conflicting results on the determinants of BI. For instance, PU was generally found to be a major contributor to BI, but, sometimes, it was found to be incapable of predicting specific measures of BI (Nordhoff et al., 2017). The major discrepancy in these studies relates to the importance of PEU (i.e., effort expectancy) to BI: Choi and Ji (2015) found PEU as a weak predictor; Madigan et al. (2017) and Moták et al. (2017) reported that PEU is a non-significant predictor; and Nordhoff et al. (2017) and Lee et al. (2017) found that PEU is not a steady predictor and it could influence specific measures of BI. A clear understanding of the importance of PEU to BI is essential, because it can influence the way the AVs are designed for users.

2.2. Research aims and hypotheses development

The objective of this research study is two-fold. As a large-scale field study is proposed by inviting participants to directly experience the self-driving mode of AV, the question that naturally arises here would be: *What are the influences of the AV experience?* Securing answers to this question is the first objective. Studies on the influence of experience are few in the literature, but even those few studies report somewhat mixed results. In their small-scale study, Moták et al. (2017) reported that the AS experience increased participants' PU and positive affective attitude toward the AS; Payre et al. (2016), based on their experimental study on a simulator of fully automated driving, found that the simulator experience did not increase acceptability of fully automated driving, and, on the contrary, it decreased participants' interest in using it under impaired driving conditions (e.g., after being tired).

In this study, attention is directed to other influences of direct experience, which were largely ignored by acceptance research: influences on the relation between beliefs, affects, and behaviors. The Elaboration Likelihood Model (ELM) (Petty and Cacioppo, 1986), in attitude and persuasion research, suggests that exposure to certain information (which is usually used in online surveys) and direct experience would produce different results in attitude formation. Direct experience can help people to assess the object-relevant information and lead them to engage more careful and effortful processes, arrive at a reasoned attitude and calibrate their beliefs and perceptions, and display greater consistency in beliefs, affects, and behaviors; on the contrary, exposure to certain information may lead people to engage less effortful processes (Petty and Cacioppo, 1986). The present field study not only considers whether direct experience leads to changes in trust, PU, PEU, and BI (see Fig. 1), but also tests whether it increases the association of BI with its psychological determinants. In addition, as reviewed above, existing AV studies report mixed results on the importance of PEU to BI. The present field study offers an opportunity to observe the dynamic influence of PEU on BI.

The second and primary aim is to explain and predict public acceptance of AVs based on the field data and to test the proposed model (see Fig. 1). The traditional TAM model (Davis, 1989) was taken as the base model, because of the following two reasons. First, TAM was adopted by previous researchers on AVs (Lee et al., 2017; Moták et al., 2017) and in-vehicle technologies (Park and Kim, 2014; Rahman et al., 2017). Second, it has a relatively high performance in explaining driver acceptance of new in-vehicle technologies (Rahman et al., 2017). In the context of AVs, two factors, namely perceived safety while riding in the AV and trust in this technology, are highlighted for incorporation in TAM. Considering that driving is a safety-critical activity and AV is an emerging technology, people's safety perception of and initial trust in this technology would play a critical role in shaping their acceptance of AVs. Two acceptance measures (BI and WTR) were considered, which enabled checking whether the determinants under consideration can be steady predictors of AV acceptance. Theoretical foundations and empirical evidence for the relations in this model

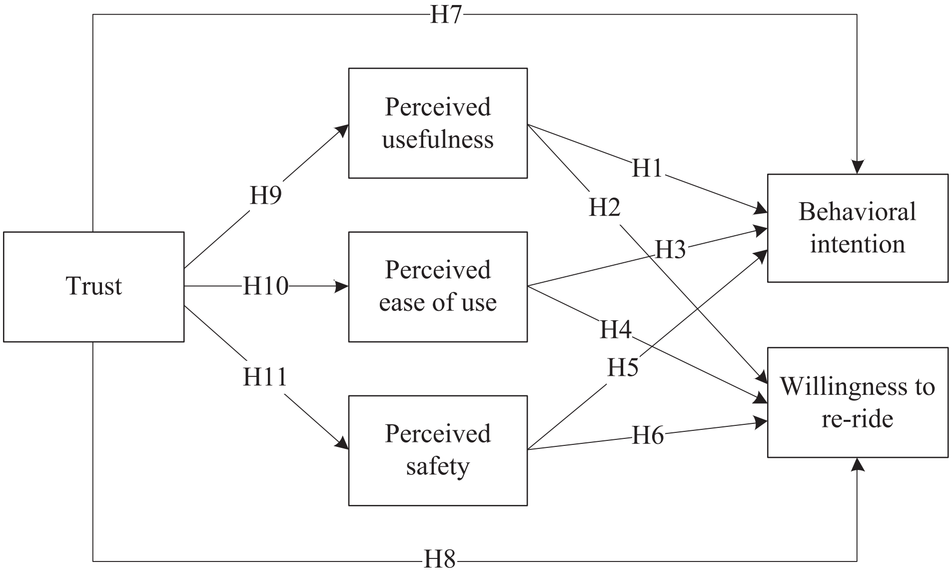

Fig. 1. Structural model for explaining acceptance of automated vehicles.

will be described in the following subsections.

2.2.1. Perceived usefulness and perceived ease of use

In TAM, PU and PEU are the two external variables that contribute largely to technology acceptance. Davis (1989) defined PU as "the degree to which a person believes that using a particular system would enhance his or her job performance" (p. 320). By definition, PU describes the extent to which the system is capable of being used advantageously. It is very close to performance expectancy in UTAUT (Venkatesh et al., 2003). Davis (1989) referred PEU to "the degree to which a person believes that using particular system would be free of effort" (p. 320). In other words, it can be understood as the opposite of the difficulty people perceive in using the system. It is similar to perceived behavioral control in TPB (Ajzen, 1991) and effort expectancy in UTAUT (Venkatesh et al., 2003).

Previous research consistently supports the positive relation between PU/PEU and technology acceptance (Davis, 1989; Davis et al., 1989; Ghazizadeh et al., 2012; King and He, 2006; Rahman et al., 2017; Venkatesh et al., 2003). Behind this relation is the cost-benefit paradigm in behavioral decision research (Payne et al., 1992). PU is closely related to perceived benefit, and PEU to perceived cost. Humans pursue the decision with high benefits and low costs. Given the wide variety of technologies, applications, and systems for which TAM has been validated, the AV acceptance should also adhere to these relations. However, as reviewed in Section 1, the importance of these two beliefs (especially, that of PEU) to AV acceptance is not so straightforward as TAM may suggest. The present field study will first examine the following hypotheses:

H1-2: PU is positively related to BI (H1) and WTR (H2).

H3-4: PEU is positively related to BI (H4) and WRT (H4).

2.2.2. Perceived safety

The pressing need to ensure safety of drivers/passengers and other road users, and reduction in traffic crashes caused by humans, has motivated the development of AVs. Safety is one of the main selling points of AVs (Fagnant and Kockelman, 2015). However, for humans, the AVs are linked with risks, uncertainty, and loss of control (Kyriakidis et al., 2015). Driving is a safety-critical activity. While riding in the AV, people have to entrust their safety to the automated system. They would place higher demand for safety in automated driving than in self-driving (Waycaster et al., 2018). Our previous study (Liu et al., in press) found that the public think SDVs should be four to five times as safe as conventional human-driven vehicles. If people cannot perceive sufficient safety from their riding in AVs, they cannot be expected to accept and adopt AVs. In fact, several public opinion surveys (Bansal et al., 2016; Dong et al., in press; Howard and Dai, 2014; Kyriakidis et al., 2015) lead to the conclusion that many people feel highly concerned about safety and security issues on AVs, which may lead them to be unwilling to ride in AVs (Dong et al., in press). The critical role of enhancing perceived safety in fostering public acceptance of AVs has been highlighted in certain studies (Salonen, 2018; Shariff et al., 2017); however, to the best of our knowledge, no empirical study has examined the influence of perceived safety on AV acceptance.

For this study, perceived safety (PS) is defined as a climate in which drivers and passengers can feel relaxed, safe and comfortable, while driving. Empirical evidence (Delbosc and Currie, 2012) shows that PS is an important predictor of intention to use public transport. In the AV context, people's safety perception is even more important, given the people's high concern for safety in this technology. In this study, if participants perceive higher safety in experiencing the AV, they may have higher intention to use AVs in future and higher willingness to ride again in the AV they travelled. Therefore, the two following hypotheses are suggested:

H5-6: PS is positively related to BI (H5) and WTR (H6).

2.2.3. Trust

Trust is "a psychological state comprising the intention to accept vulnerability based on upon positive expectations of the intentions or behavior of another" (Rousseau et al., 1998, p. 385). Trust is fundamental to human–automation interaction (Lee and Moray, 1994; Lee and See, 2004). The interaction between humans and automation is mediated by trust (Ghazizadeh et al., 2012). Trust in automation has been found to affect acceptance, utilization, and reliance behaviors (Lee and Moray, 1994; Lee and See, 2004; Merritt and Ilgen, 2008; Parasuraman and Riley, 1997); it is the psychological precursor to engaging in reliance activities. Trust in AVs is defined here as the belief that permits the public and potential consumers to willingly become vulnerable to AVs.

Although the trust concept was not originally considered by TAM (Davis, 1989) or its successors (Venkatesh et al., 2003; Venkatesh et al., 2012), several later studies (Ghazizadeh et al., 2012; Hengstler et al., 2016; Pavlou, 2003) consider that incorporating trust into TAM is necessary, especially in conditions of high risk and uncertainty. Pavlou (2003) integrated trust and perceived risk with TAM in e-commerce research and hypothesizes that trust can directly affect BI or indirectly affect BI through the mediating effects of PU, PEU, and perceived risk. Adopting the hypothesis of Pavlou (2003), Ghazizadeh et al. (2012) extended TAM to the Automation Acceptance Model to explain automation adoption, and suggest that trust in automation can be a direct determinant of BI and also an indirect determinant through PU and PEU. Choi and Ji (2015) applied these models to survey laypeople's BI to use AVs.

Trust in a technology, as an affective response, might create the willingness required to accept and use the technology (Lee and See, 2004; McKnight et al., 2002). The direct role of consumer's trust in forming his or her intention to use applications in information systems and e-commerce has been tested and confirmed by many studies (Gefen et al., 2003; McKnight et al., 2002; Pavlou, 2003). Similarly, the level of trust determines how widely the AVs would be adopted by consumers (Shariff et al., 2017). If people do not have sufficient confidence in AVs, then they cannot benefit from them effectively. Thus, sufficient public trust is regarded as a necessary precondition for mass adoption of AVs (Noy et al., 2018; Shariff et al., 2017). This leads to the following hypotheses:

H7-8: Trust is positively related to BI (H7) and WTR (H8).

Fig. 2. Xinda AV (developed by Chang'an University).

Trust may influence the cognitive processes of forming and weighing technology-related PU and PEU beliefs that eventually lead to an evaluative judgment of whether or not to accept the technology. Thus, trust might indirectly impact on BI through the mediating effects of PU and PEU (Choi and Ji, 2015; Ghazizadeh et al., 2012; Nordhoff et al., 2016; Pavlou, 2003). In addition, one particular role played by trust is to reduce perceptions of risk and uncertainty (Hengstler et al., 2016; Rousseau et al., 1998). Previous studies (Choi and Ji, 2015; Pavlou, 2003) reported the effect of trust on attenuating perceived risk. People who trust the dependability of AV technology might be more likely to overcome their risk perceptions toward this technology. Therefore, a high level of trust may be able to enhance safety perception in utilizing AVs. This leads us to examine the following hypotheses:

H9-11: Trust is positively related to PU (H9), PEU (H10), and PS (H11).

3. Methodology

The four components (trust, PU, PEU, and BI), shown in Fig. 1, are related to SDVs. As no SDV (SAE Level 5) is available for road tests at present, let alone for academic field studies, the author had to compromise on using an AV with a lower automation level to enable the participants to directly experience the self-driving mode of the AV, under different traffic scenarios. By following this approach, the participants were expected to calibrate their perceptions and judgments of SDVs.

3.1. Apparatus and scenario design

Fig. 2 shows the experimental AV—Xinda AV, which is equipped with a high-resolution stereo camera rig (Basler Ace1600 GigE, image size: 1200 × 800 pixels), a LiDAR (Velodyne HDL-32E) and a differential GPS (RT-GPS/INS). Xinda was originally a passenger car manufactured by BYD auto group, China, which is rebuilt for the purpose of scientific research and experiments. Xinda is of SAE Level 3: the automated system can both conduct some parts of the driving task and monitor the environment in certain conditions and the human driver must be ready to take back control when the automated system requests (SAE, 2014). Xinda performs five types of functions: (1) sensing and locating; (2) global route planning; (3) behavior reasoning; (4) trajectory planning; and (5) trajectory tracking control. When a planned destination is given to Xinda, it will calculate a feasible route from the known traffic networks and start following the planned route. As it runs, Xinda can perceive any stationary or moving object emerging on the route and control its direction and speed to avoid any possible collision.

An automated vehicle testing track (AVTT) is built on Chang'an University Cooperative Vehicle-Infrastructure System (CU-CVIS) test-bed (see Fig. 3). The CU-CVIS includes a 2.4 km long, high-speed circular test road with 2 lanes and an extra 1.1 km long, straight 4-lane test track, with 4 kinds of pavements (asphalt, concrete, bricks, and dirt). It is a comprehensive and closed environment for testing various connected and automated vehicle (CAV) applications.

The AVTT was designed to provide a 1 km long track, with nine typical driving scenarios (see Table 1), which were marked "S1" to "S9", as shown in Fig. 3. S1 (pedestrian collision avoiding) and S9 (going through a snake-shape barrier) are illustrated in Fig. 4.

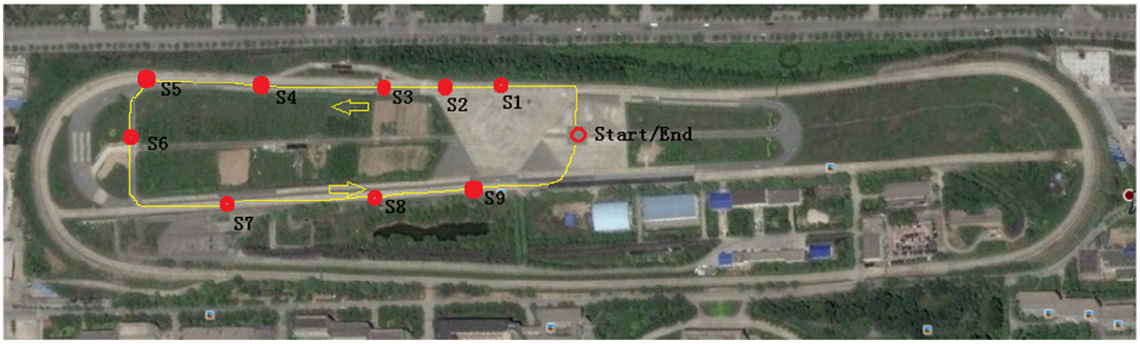

Fig. 3. Chang'an University Cooperative Vehicle-Infrastructure System test-bed.

Table 1
The description of the nine driving scenarios.

Scenario	Duration	Description
S1: Pedestrian collision avoiding	20 s	The AV stops when a fake pedestrian is going across the track
S2: Bicycle collision avoiding	20 s	The AV stops when a fake cyclist is going across the track
S3: Traffic signal recognition	25 s	The AV recognizes the status of the traffic signal and decides whether to pass through or not
S4: Forward collision avoiding	20 s	A human-driven vehicle is stopping in the front of the AV; the AV detours on it
S5: Curve speed warning	25 s	The AV receives speed limit information from the roadside facility, and follows the recommended speed
S6: Emergency vehicle preemption	50 s	An emergency vehicle (EV) is passing through the intersection with priority; the AV stops on the stop line until the EV passes away and the signal turns green
S7: Going through a tunnel	30 s	The AV goes through a tunnel without the guidance from the Global Positioning System
S8: Overtaking a moving human-driven vehicle	40 s	The AV overtakes a human-driven vehicle
S9: Going through a snake-shape barrier	10 s	The AV goes through a snake-shape barrier made up of traffic cones

Fig. 4. Scenarios of S1 (pedestrian collision avoiding; left) and S9 (going through a snake-shape barrier; right).

3.2. Measures

Table 2 presents the six constructs (trust, PU, PEU, PS, BI, and WTR) and their items. All items were measured on Likert-type scales (*totally disagree* = 1 and *totally agree* = 5). Trust, PU, PEU, and BI are related to SDVs. PS is the perception of safety level experienced while riding in the AV, and WTR measures the extent to which the participants were willing to ride in the AV again.

3.3. Participants and procedure

Three-hundred undergraduate students participated in the experiment voluntarily. Among them, 171 were males (57.0%), 76 held valid driving licenses (25.3%), and 283 (94.3%) had heard of SDVs before. They were recruited from classes and through emails and social media. All the participants gave their written informed consent. The study was approved by Chang'an University.

The study was conducted with small batches of two or three participants per session. First, the participants had to read the experiment's introduction, sign the informed consent, read the introduction to SDVs, respond how they perceive SDVs, and give their demographic information in a quiet experimental room. During the experiment, the test driver drove the vehicle for the first five to ten seconds and initiated the automation mode. Then, the AV drove through all the scenarios in the self-driving mode. A human-driven vehicle monitored and recorded the AV for safety reasons, maintaining safe distance. The participants were encouraged to ask questions about the operations and functions of the AV and future SDVs. The AV finally stopped at the starting point with the test

Table 2
Constructs, their items, and sources.

Construct and item	Source
Trust	
Trust1: I think SDV is dependable.	Modified from Choi and Ji (2015)
Trust2: I think SDV is reliable.	
Trust3: Overall, I can trust SDV.	
Perceived usefulness	
PU1: I think using SDV can make my driving easier	Modified from Davis (1989) and Gefen et al. (2003)
PU2: I think using SDV can improve my driving safety performance	
PU3: I think using SDV can allow me to do other things in driving	
PU4: Overall, SDV is useful for me	
Perceived ease of use	
PEU1: I think SDV is easy to learn	Modified from Davis (1989) and Gefen et al. (2003)
PEU2: I think SDV is easy to control	
PEU3: I think SDV is easy to understand	
PEU4: Overall, I think SDV is easy to use	
Perceived safety	
PS1: I felt relax during riding in the AV	Self-developed
PS2: I felt safe during riding in the AV	
PS3: I felt risky during riding in the AV (reverse-scaled item)	
Behavioral intention	
BI1: I intend to ride in an SDV in the future	Modified from Choi and Ji (2015) and Gefen et al. (2003)
BI2: I intend to buy an SDV in the future	
BI3: I will recommend family members and friends to ride in an SDV	
Willingness to re-ride	
I am willing to ride in this AV again	Self-developed

driver's help. Later, the participants were led back to the experimental room, where they were asked to complete a *post-hoc* questionnaire regarding their perceptions and acceptance of the AV and future SDVs. Finally, each of the participants was given a monetary reward of $6. A sample video of the field experiment can be provided upon request. The data used in this paper was extracted from the *prior* and *post* questionnaires.

The field experiment was carried out on sunny days between July and October 2017. All through the experiment, the same AV was used to ensure consistency in the participants' experience of AV. For safety reasons and also because of the complexity of the traffic scenarios (e.g., waiting for the green signal in S3 and the emergency vehicle in S6), the AV had to operate at a rather low speed in the self-driving mode, the average speed being 20 km/h and the preset maximum speed being 40 km/h. This AV experience lasted 4.5 to 5 min. During the experiment, the test driver's hands were off the steering wheel, but he was ready to take over control of the AV, whenever necessary; in fact, no manual intervention occurred in the whole field experiment. Each participant had one time of riding.

4. Results

4.1. Measurement model

The structural equation modeling (SEM) technique of Partial Least Squares (PLS) was adopted to test the measurement and structural models. PLS-SEM is considered suitable for analyzing complex path models (Hair et al., 2014). It is not impeded by stringent and impractical assumptions (e.g., the multivariate normality assumption) and less demanding in sample size (Hair et al., 2014). The R package *plspm* (Sanchez, 2013) was used to execute the PLS-SEM analysis, following the bootstrapping procedure (1,000 subsamples).

Indicator reliability, internal consistency reliability, convergent validity, and discriminant validity of the measurement model were examined, before and after the participants' AV experience, separately (see Table 3). These criteria do not involve WTR, because WTR was measured by a single item. Two items (PU3 and PS3) were deleted because of their low factor loadings ($< .70$). In the final measurement, all items' factor loadings are above .70, confirming indicator reliability. All composite reliability (CR) and Cronbach's alpha values are greater than .70, confirming internal consistency reliability. All average variance extracted (AVE) values exceed the criterion of .50 (Fornell and Larcker, 1981), establishing convergent validity. The square root of each AVE (shown on the diagonal in Table 4) is greater than the associated inter-construct correlations (shown, off the diagonal, in Table 4), confirming discriminant validity. The variance inflation factors (VIFs) of the constructs are below 3.0, indicating the absence of multicollinearity (Hair et al., 2014). Thus, the reliability and validity of the measurement model are adequate.

Comparison of the mean values of four constructs, measured before and after the participants' AV experience, shows significant increase in trust ($\Delta M = 0.08$, $p = .013$), PEU ($\Delta M = 0.12$, $p < .001$), and PU ($\Delta M = 0.08$, $p = .012$) after AV experience, but no change in BI ($\Delta M = 0.02$, $p > .05$). The ELM theory (Petty and Cacioppo, 1986) suggests that direct experience will increase the

Table 3
Reliability and validity of the measurement model.

Construct	Item	Before experiencing the AV					After experiencing the AV				
		M (*SD*)	FL	α	CR	AVE	*M* (*SD*)	FL	α	CR	AVE
Trust	TT1	3.77 (0.74)	.91	.86	.92	.78	3.83 (0.67)	.93	.91	.94	.85
	TT2	3.66 (0.72)	.90				3.80 (0.69)	.94			
	TT3	3.88 (0.68)	.85				3.92 (0.66)	.89			
PU	PU1	3.78 (0.73)	.77	.73	.85	.64	3.85 (0.72)	.84	.80	.88	.72
	PU2	3.39 (0.88)	.83				3.54 (0.90)	.84			
	PU4	3.91 (0.68)	.81				3.93 (0.70)	.87			
PEU	PEU1	3.74 (0.77)	.88	.88	.92	.74	3.89 (0.71)	.89	.91	.94	.79
	PEU2	3.70 (0.74)	.87				3.78 (0.77)	.91			
	PEU3	3.70 (0.78)	.86				3.87 (0.75)	.90			
	PEU4	3.84 (0.66)	.82				3.93 (0.73)	.86			
PS	PS1						3.53 (0.81)	.86	.71	.87	.77
	PS2						3.59 (0.75)	.89			
BI	BI1	3.64 (0.76)	.89	.88	.92	.80	3.63 (0.80)	.93	.90	.94	.83
	BI2	3.52 (0.77)	.93				3.56 (0.78)	.93			
	BI3	3.48 (0.75)	.86				3.48 (0.80)	.88			

Note: *M*, mean; *SD*, standard deviation; FL, factor loading; α, Cronbach's alpha; CR, composite reliability; AVE, average variance extracted. PU, perceived usefulness; PEU, perceived ease of use; BI, behavioral intention; PS, perceived safety.

Table 4
Mean (standard deviation) and zero-order correlation between constructs before and after experiencing the AV.

Construct	*M* (*SD*)	1	2	3	4	5
Before experiencing the AV						
1. Trust	3.77 (0.63)	(.89)				
2. Perceived usefulness	3.69 (0.62)	.49	(.80)			
3. Perceived ease of use	3.74 (0.63)	.44	.50	(.86)		
4. Behavioral intention	3.54 (0.68)	.53	.52	.40	(.89)	
After experiencing the AV						
1. Trust	3.85 (0.62)	(.92)				
2. Perceived usefulness	3.77 (0.66)	.60	(.85)			
3. Perceived ease of use	3.87 (0.66)	.53	.66	(.89)		
4. Behavioral intention	3.56 (0.73)	.56	.69	.59	(.88)	
5. Perceived safety	3.56 (0.68)	.54	.53	.44	.51	(.91)
6. Willingness to re-ride	4.05 (0.72)	.51	.54	.39	.53	.50

Note: Numbers in parentheses are the square roots of AVEs. The off-diagonal elements are the correlations between constructs. All correlations were significant at .001.

consistency among affects, beliefs, and behaviors. That is, for this study, the AV experience was assumed to increase the correlations among the four constructs (trust, PU, PEU, and BI). As expected, all the correlations of pairwise constructs increased (see Table 4). Then, the Fisher r-to-z transformation was used to assess the significance of correlation changes. The correlations between PU and PEU ($\Delta R = .17$, $z = 3.07$, $p = .002$), PU and BI ($\Delta R = .17$, $z = 3.33$, $p < .001$), and PEU and BI ($\Delta R = .19$, $z = 3.06$, $p = .002$) increased significantly, whereas that between Trust and PU increased only marginally ($\Delta R = .11$, $z = 1.87$, $p = .062$). No change is found in the correlations between Trust and PEU ($\Delta R = .10$, $z = 1.51$, $p = .130$) and Trust and BI ($\Delta R = .03$, $z = 0.36$, $p = .716$). The significant or marginal increase in four out of six correlations suggests that the AV experience increased the consistency among the constructs involved.

4.2. Structural model

Three structural models were run for this study. First, the two TAM models (before and after the AV experience) were tested and compared to assess the influence of direct experience, at the structural model level. Then, the complete structural model (see Fig. 1) was examined to identify the psychological determinants of BI and WTR, after the participants' AV experience.

4.2.1. TAM

First, trust was added to the traditional TAM (Davis, 1989; Davis et al., 1989) and then PLS analysis was run for this TAM model based on the data collected before and after the participants experiencing the AV, separately. Three types of comparisons were made. First, the significance of these paths (see Table 5) was checked, and it is found that the AV experience led PEU to be a significant predictor of BI. Second, a bootstrap t-test (Sanchez, 2013) was executed to compare the path coefficients. The two models exhibited three different paths: PU → BI (H1: $\Delta\beta = 0.15$, $p = .039$), trust → BI (H7: $\Delta\beta = -0.17$, $p = .017$), and trust → PU (H9: $\Delta\beta = 0.11$,

Table 5
Path coefficient (β) and R^2 in the TAM before and after the AV experience.

Path	β (before the AV experience)	β (after the AV experience)	$\Delta\beta/\Delta R^2$
H1: PU → BI	.32***	.47***	.15*
H2: PEU → BI	.10	.20***	.10
H7: Trust → BI	.33***	.16**	-.17*
H9: Trust → PU	.51***	.62***	.11*
*H*10: Trust → PEU	.44***	.54***	.10
R^2 of PU	.26	.38	.12 [.01, .25][a]
R^2 of PEU	.19	.29	.10 [-.02, .21][a]
R^2 of BI	.39	.54	.15 [.03, .26][a]

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
[a] 95% confidence intervals.

$p = .017$). The correlation between trust and BI did not change ($\Delta R = .03$) (see Table 4), but their path coefficient decreased ($\Delta\beta = -0.17$), possibly because the AV experience intensified the influence of PU and PEU on BI (Note: the correlation between PU/PEU and BI increased significantly as shown in Table 4). Third, the differences between the proportions of the explained variance (R^2) of PU, PEU, and BI were compared, before and after participants' AV experience, following Olkin and Finn's approach (1995). The 95% confidence interval of ΔR^2 for PU ($\Delta R^2 = .12$) and BI ($\Delta R^2 = .15$) did not cover zero (see Table 5), indicating that direct experience significantly increased the explanatory power of PU and BI.

4.2.2. Complete structural model

The following analyses, including the mediation and prediction analyses, are specific to the complete structural model (see Fig. 1). As shown in Fig. 5, the results support all the hypotheses excepting one, namely that PEU was not a significant predictor of WTR (H4: $\beta = -.05$, $p = .422$).

For the complete structural model, the R^2 values for BI and WTR were 0.55 and 0.40, greater than the cutoff value of 0.10 (Falk and Miller, 1992). For PU, PEU, and PS, all R^2 values were greater than 0.50. Thus, the research model had acceptable explanatory power for all endogenous variables.

The Goodness-of-fit (*GoF*) criterion (Tenenhaus et al., 2005) is used as a global fit measure of PLS, ranging from 0.00 to 1.00. The *GoF* is defined as the geometric mean of the AVE and average R^2 for endogenous variables. The *GoF* criteria are 0.10, 0.25, and 0.36 for small, medium, and large effect sizes, respectively (Wetzels et al., 2009). The *GoF* was calculated as 0.55, greater than the cutoff value of 0.36 for the large effect size.

We added trust and PS to the traditional TAM model and compared with the new model with the traditional TAM (PU and PEU were two predictors). The increased R^2 value of the new model was 0.03 for BI ($F_{(2, 293)} = 17.6, p < .001$) and 0.10 for WTR ($F_{(2, 293)}$

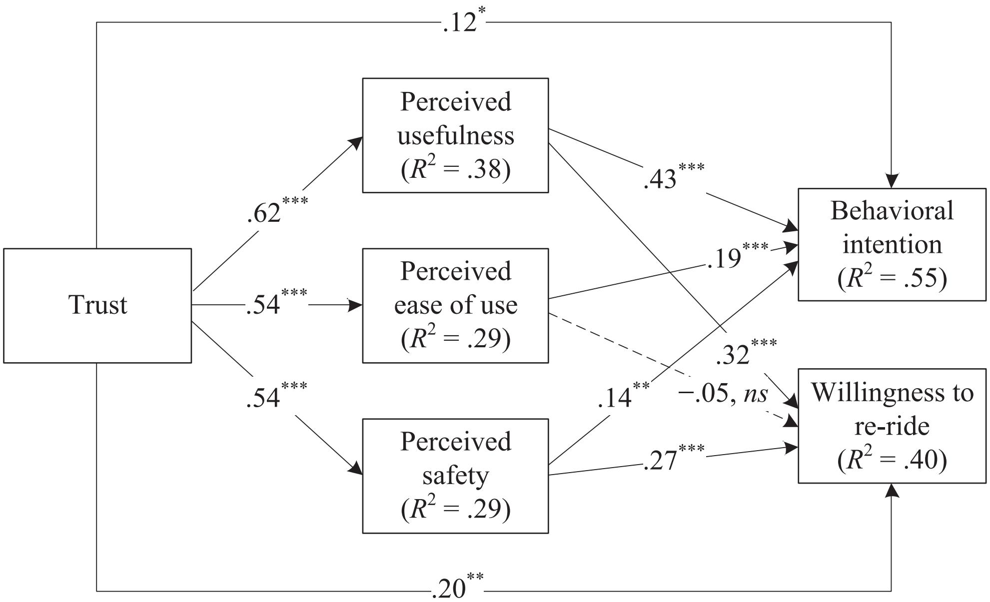

Fig. 5. Result of PLS analysis for the complete structural model. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; *ns*, not significant (dashed line).

Table 6
Indirect and direct effects of trust.

Acceptance	Indirect effect of trust				Total indirect effect	Direct effect
	Mediators	*f*	Sobel *z*	VAF		
Behavioral intention	Perceived usefulness	0.27***	6.45	70%	0.44	0.12
	Perceived ease of use	0.10***	3.28	46%		
	Perceived safety	0.07**	2.72	39%		
Willingness to re-ride[a]	Perceived usefulness	0.20***	4.45	50%	0.32	0.20
	Perceived safety	0.15***	4.45	43%		

Note: *f*, indirect effect; VAF, variance accounted for.
[a] PEU was not considered a mediator because it had a non-significant relation with WTR in PLS.

= 47.1, $p < .001$). Thus, adding trust and PS to TAM proved to be meaningful, especially for explaining WTR.

Previous surveys (Abraham et al., 2017; Dong et al., in press) suggested that people's perception and attitude toward AVs are linked to their socio-demographic characteristics. Liu et al. (2018) suggested that the heterogeneity in these characteristics needs to be taken into account while designing and applying new transportation technologies. There is thus a need to consider the influence of demographic variables. Three demographic variables of the participants were collected including gender, whether they had heard of SDVs before, and whether they held a valid driving license. After controlling for the effect of these demographic variables on all the six constructs in the model, the structural model in Fig. 5 was rechecked. It is found that these demographic variables were not associated with any construct in the model ($ps > 0.05$) and that they did not affect the findings in Fig. 5.

Finally, following Peng and Lai's suggestion (2012), the ordinary least squares (OLS) regression analysis was carried out to check the robustness of the PLS results. The average values of constructs were calculated and subjected to OLS analysis. The OLS results are found to be, by and large, consistent with the PLS results, supporting the robustness of the PLS results. The OLS results can be made available upon request.

4.3. Mediation analysis

Trust is assumed to indirectly influence acceptance through PU, PEU, and PS. Sobel *z*-test (Sobel, 1982) was performed and Preacher and Hayes' procedure (2008) was followed to check the indirect effect of trust in the complete model. The variance accounted for (VAF) was calculated to determine the strength of the indirect effect (i.e., mediating effect) in relation to the total effect (i.e., direct effect + indirect effect). For determining mediation, a rule of thumb (Hair et al., 2014) was applied: VAF > 80%, full mediation; VAF ≤ 80%, partial mediation; VAF < 20%, no mediation. Table 6 shows that PU, PEU, and PS were meaningful mediators ($ps < .01$) in the trust-BI relation. Their VAF values ranged from 39% to 70%, which were more than the 20% threshold level, indicating partial mediation in the trust-BI relation. Similarly, PU and PS were meaningful mediators ($ps < .001$ and VAFs > 20%) in the trust-WTR relation. Compared with other mediators, PU accounted for more indirect effects of trust. The indirect effect of trust was higher than its direct effect on both acceptance measures (see Table 6).

4.4. Prediction analysis

Evaluating predictive performance is recognized as useful for theory building and validation purposes (Shmueli et al., 2016). The predictive capacity of the research model in Fig. 1 was checked through the following steps (Cepeda Carrión et al., 2016): (1) divided the sample randomly into a training sample ($n = 200$) and a holdout sample ($n = 100$); (2) PLS analysis was carried out for the training sample and the weights and path coefficients were estimated; (3) standardized each observation in the holdout sample; (4) estimated the observed scores for the holdout sample as linear combinations of the respective observations by using the weights obtained from the training sample; (5) standardized the observed scores; (6) predicted the scores for the endogenous constructs as linear combinations of observed scores of predictors and the path coefficients obtained from the training sample; and (7) used three criteria to determine how well the PLS model performs. The first criterion requires that the correlation (R) between the predicted and the observed scores be significant (Ali et al., 2016). The second criterion requires that the R^2 values from the holdout and training samples be similar (Cepeda Carrión et al., 2016). The final one is the Theil's measure for forecast quality (U_2) (Theil, 1966), $U_2 = \sqrt{\sum (P_i - A_i)^2} / \sqrt{\sum A_i^2}$ (P_i and A_i denote the predicted and actual standardized scores for the observation i, respectively), which requires that the U_2 value be lower than 1, failing which the predictive model will be considered to be no better than a naïve no-change model.

The out-of-sample prediction was run five times, and the results are shown in Table 7. All R^2 values from the holdout sample were significant ($ps < .001$) and similar to those from the training sample (see their mean R^2 values). All U_2 values were lower than 1. Thus, the results confirm the predictive performance of the proposed model. The predictive capacity of this model for BI is better than that for WTR (see the higher R^2 and lower U_2 values for BI).

Table 7
Results of out-of-sample prediction.

k	R^2 from the holdout sample					R^2 from the training sample					Theil U_2 statistic				
	PU	PEU	PS	BI	WTR	PU	PEU	PS	BI	WTR	PU	PEU	PS	BI	WTR
1	.34	.31	.21	.45	.29	.40	.27	.34	.59	.46	.82	.83	.90	.75	.85
2	.30	.34	.24	.49	.36	.42	.27	.32	.57	.41	.84	.82	.87	.71	.80
3	.35	.18	.31	.50	.45	.40	.35	.28	.57	.39	.81	.91	.83	.71	.74
4	.35	.22	.28	.57	.50	.40	.35	.31	.55	.36	.81	.89	.85	.66	.71
5	.24	.21	.29	.44	.39	.44	.32	.30	.59	.42	.88	.89	.85	.75	.78
M	.32	.25	.27	.49	.40	.41	.31	.31	.57	.41	.83	.87	.86	.72	.78
SD	.05	.07	.04	.05	.08	.02	.04	.02	.02	.04	.03	.04	.03	.04	.06

5. Discussion

5.1. Theoretical implications

Some of the foregoing results of the influence induced by direct experience on the four constructs of SDVs are rather intriguing. The ELM theory (Petty and Cacioppo, 1986) in attitude and persuasion research suggests two kinds of influence. First, the direct experience expects to help people in assessing object-relevant information that leads them to engage more careful and effortful processes, and in forming attitudes, beliefs, or BI in a rather objective manner. The AV experience might play a more important role in re-shaping the two cognitive beliefs (PU and PEU), which are closely related to the operation of this emerging technology. In this study, the direct experience did lead to a significant (though not very large) increase in trust, PU and PEU (but not BI), relating to SDVs. A simulator study (Payre et al., 2016) of fully automated driving (FAD, SAE Level 5) also showed that the simulator experience did not increase FAD's contextual acceptability; instead, it decreased participants' interest in using FAD under impaired driving conditions (e.g., while the drivers are tired). Several reasons might be cited to explain why direct experience (or simulator experience) could not largely increase people's positive beliefs and BI, relating to AVs. For example, the current AVs (like the one used in this study) or their simulators (Payre et al., 2016) might not be perfect enough technically, and/or people might have had high expectations of AVs because of the hype created by the social media and other information resources.

Second, ELM suggests that direct experience may increase affect-belief-behavior consistency (that is, affect and belief are more likely to predict behaviors), which is of great interest for the objectives of this study. In this case, as suggested by ELM, direct AV experience increased the correlations between PU/PEU and BI, and the explanatory power of PU (by trust) and BI (by trust, PU, and PEU). Particularly, as a non-significant predictor of BI before the AV experience, PEU contributed to predict BI after the AV experience, which will be discussed in the foregoing paragraphs. Put simply, the direct experience with the AV increased the participants' trust, PU, and PEU, relating to SDVs, and particularly led PU and PEU beliefs to being more predictive of BI.

Public acceptance of AVs was explained and predicted based on the field data, which is expected to produce more realistic findings than the previous survey-based studies. The proposed complete model accounted for 55% of the variability in BI and 40% in WTR after the participants' experiencing of the AV, indicating its satisfactory explanatory power for these two AV acceptance measures. This model also has acceptable predictive power, as confirmed by the out-of-sample prediction. All predictors, including the two factors (PU and PEU) of the original TAM (Davis, 1989) and the two added factors (PS and trust), induced considerable impact on AV acceptance.

Previous studies recognized PU (or performance expectancy) as one of the major determinants of BI in using automated road transport systems (Madigan et al., 2017), ASs (Moták et al., 2017), and self-driving cars (Choi and Ji, 2015; Lee et al., 2017). The present field study corroborates this finding. Furthermore, PU is found to be a strong predictor of WTR. It even carried the highest weights in forming both acceptance measures. Other studies (Park and Kim, 2014; Rahman et al., 2017) also report the dominant role of PU in shaping people's BI in using in-vehicle information and automation technologies.

Our result on PEU can clarify the conflicting results on the importance of PEU to BI in the AS/AV literature. PEU has been reported as a weak predictor of BI in using autonomous vehicles (Choi and Ji, 2015), a non-significant predictor of BI in using ASs (Madigan et al., 2017; Moták et al., 2017), and a weak (but not steady) predictor in influencing specific measures of BI (Lee et al., 2017; Nordhoff et al., 2017). An interesting finding reported here is that PEU was a significant predictor of BI only when the participants had the AV experience. Online surveys, involving participants with little or no experience, have certain limitations (Nordhoff et al., 2017; Rahman et al., 2017). Such participants (like the participants of our study before experiencing the AV) may not have had the right mental model about AVs (Körber et al., 2018), and hence, their PEU (i.e., perceived difficulty) might not predict BI or weakly predict BI as found in previous surveys (Choi and Ji, 2015; Lee et al., 2017; Moták et al., 2017) or in our *prior* data. That PEU is a significant predictor of BI, if the participants had the AV experience, has not been supported by a recent field study on ASs (Madigan et al., 2017). This contradiction can be explained as due to the difference between public ASs and private AVs. The users cannot operate public ASs or they put in a little effort to ride in them; thus, their PEU may not be an important factor in their decision to use ASs (Madigan et al., 2017). On the contrary, in operating private AVs, the users (i.e., drivers) have to invest more effort in controlling the automated system. The participants of this study could see how the test driver switched from manual control to automation control, and again back to manual control. This particular experience affected the participants' PEU relating to SDVs and resulted in

PEU becoming critical factor in influencing the participants' intention to use SDVs. In addition, the participants' PEU was not linked with their WTR, probably because, they acted as passengers in the AV, and thus their willingness to re-ride in that AV need not be associated with their perceived difficulty in operating AVs.

Safety being one of the basic human needs, people and regulatory authorities place highly exacting requirements on transportation safety. Feeling a high level of safety is a necessary precondition for people before they accept to use AVs. Previous studies did not investigate the influence of PS on people's intention to use and willingness to ride in AVs. Because AVs are not yet available in the market, it is difficult to obtain feedback from the public on their experience of safety while riding in AV. Although Salonen's study (2018) provides data on passengers' perception of traffic safety in a self-driving bus, it did not explore how PS influences passengers' acceptance of the bus. The field design proposed here clearly demonstrates the positive and strong influence of PS on both BI and WTR. PS was more influential on WTR than on BI (see Fig. 5).

Trust is fundamental to human–automation interaction (Lee and Moray, 1994; Lee and See, 2004), just as to social interaction. Trust can affect acceptance, utilization, and reliance behaviors related to automation (Lee and Moray, 1994; Lee and See, 2004; Merritt and Ilgen, 2008; Parasuraman and Riley, 1997). Initial trust can create willingness to use new, unfamiliar, emerging technologies (McKnight et al., 2002). Based on this belief, trust in AV technology was assumed to be positively associated with people's intention to use AVs and rely on them (Choi and Ji, 2015; Körber et al., 2018; Noy et al., 2018; Shariff et al., 2017). As expected, trust was a critical predictor of BI and WTR. Research (Choi and Ji, 2015; Ghazizadeh et al., 2012; Pavlou, 2003) argues that trust can indirectly affect acceptance through the mediating effects of PU, PEU, and perceived risk. In the mediation analysis of this study, the indirect effect of trust was significant. If trust is considered a decision-making heuristic, then it may directly influence acceptance decisions or indirectly influence acceptance decisions by its influence on beliefs of usefulness, ease of use, and safety.

5.2. Practical implications

The field results of this study have practical implications to vehicle design and public communication to increase public acceptance of AVs. First, increasing PU is necessary in the light of the consistent finding on the importance of the usefulness of AVs people perceive in determining their intention to use AVs. Participants' responses to PU items might indicate the possible direction for increasing the PU, and this is true for other constructs too. For example, the relatively low PU2 ($M_{\text{before}} = 3.39$, $M_{\text{after}} = 3.54$) suggests that the participants were not positive about whether SDVs can improve their driving safety, and this uncertainty is in line with the current road test results, which show that SDVs' significant safety advantage over that of human drivers could not be proved so far (Favarò et al., 2018; Teoh and Kidd, 2017). The present study underlines the need for increasing technical reliability of AVs and adequate communication of AVs' benefits to the public.

The irrelevance or insignificance of PEU, as a predictor of intention to use ASs and AVs, found in previous surveys (Choi and Ji, 2015; Lee et al., 2017; Madigan et al., 2017; Moták et al., 2017), may imply that, for designing AVs, much attention need not be paid to drivers' PEU in operating AVs. On the contrary, the present results clearly show that PEU, though not a significant predictor of BI *prior* to the participants' experiencing the AV, become a significant predictor after the participants directly experienced the AV. In forming the participants' BI to use AVs in future, this factor ($\beta = .19$) may even play a more important role than PS ($\beta = .14$). Maintaining efficiency in operating AVs should be given due attention in designing the AVs.

The more safety participants perceived while experiencing the AV, the more they accepted the idea of using AVs. Although the participants with direct experience of automated driving had somewhat positive attitude toward safety in ASs (Salonen, 2018) and in the AV of this study, the high levels of concern, expressed earlier by participants in numerous online surveys, for operational safety and personal safety in using AVs/ASs cannot be ignored (Bansal et al., 2016; Dong et al., in press; Kyriakidis et al., 2015; Schoettle and Sivak, 2014), and this may become a psychological barrier to mass adoption and deployment of AVs. Thus, emphasizing the safety advantages of AVs over those of human-driving and facilitating the drivers and passengers in perceiving themselves as being highly safe while riding in AVs are important strategies to be adopted in public communication (Shariff et al., 2017).

Higher trust in AVs was linked to higher BI and WTR. Although researchers in the human–automaton interaction field caution against over-trust and over-reliance issues (Lee and See, 2004; Parasuraman and Riley, 1997), more attention should continue to be paid in addressing the current distrust issues. Public distrust may be the biggest obstacle to mass adoption of AVs (Hutson, 2017). Certain strategies are suggested to earn public trust; these include, besides others, addressing the ethical and social dilemmas and increasing the transparency in decision-making processes related to AVs (Shariff et al., 2017), and enhancing public beliefs on reliability, usability and understandability of AV technology (Hengstler et al., 2016).

5.3. Limitations of the present study and future work

The present study of AVs was constrained by several limitations. First, the participants were young college students, who tended to be more positive toward AVs and more inclined to accept AVs than old people (Abraham et al., 2017; Dong et al., in press). Old people may have a different opinion about accepting AV and its determinants. However, the inter-relationships between different factors of the proposed model may not be affected by the participants' type (King and He, 2006). Second, the participants were not required to directly maneuver the AV and the test driver was required to sit behind the wheel, for legal, ethical, and safety reasons. The participants, therefore, developed their perceptions by observing the test driver and the AV, which may be different from those developed from direct control. Third, using a Level 3 AV (conditional automation) to understand public beliefs and intentions relating to future Level 5 AVs might not be acceptable to all researchers. Going by the current legislation and status of technology development, one can predict that a Level 5 AV without human drivers may not be available in the near future for large-scale empirical studies involving human participants. As argued by Consumer Watchdog (Simpson, 2018), "[f]or now, given the state of the technology as indicated by developers themselves, any AV legislation should require a human driver behind a steering wheel capable of taking control." The AV used in this study functioned exactly as a Level 5 AV, without manual intervention, and dealt with nine different, complex traffic scenarios, enabling the participants to see how the AV works in a self-driving mode. Thus, the benefits of this field study are believed to outweigh its limitation. Compared with the previous online surveys or simulators, used for understanding public perceptions and acceptance of Level 5 AVs, this limitation will be the present study's strength in terms of research design. Fourth, only four determinants of AV acceptance were investigated, which can partly explain why the proposed model did not have high explanatory power for WTR. This study leaves room for other determinants to explain the variance of AV acceptance. Finally, in this study, only attitudinal acceptance was measured, not behavioral acceptance (i.e., actual usage). There is no guarantee that the same factors, which predict the attitudinal acceptance, can also best predict the actual usage. Once the AVs are in the market, then the actual usage measure should be adopted by future researchers.

For increasing the field knowledge of how the public responds to AVs, some avenues of research are suggested here. First, to control the potential influence of the test driver behind the wheel on participants' WTR, it may be enquired from the participants whether they are willing to re-ride in the AV, assuming that the test driver sits in the backseat. Second, the AV may be re-built to allow the test driver sit in the backseat to safely control the AV and create a verisimilar self-driving condition, and then the participants' responses to SDVs collected. Third, it is worthwhile to consider the influences of different types of individual-related (e.g., young vs. old, supporters vs. opponents), vehicle-related (e.g., no driver intervention vs. driver intervention) and scenario-related factors (e.g., short-time vs. long-time experience) on people's cognitive, affective, and behavioral responses in field studies. Fourth, future studies should consider the effects of additional socio-psychological factors (e.g., emotion) on AV acceptance and understand the antecedents of PS and trust in AVs. Public perception and attitudes toward AVs may change over time (for example, a fatality involving an AV can substantially reduce people's positive attitude and trust). Therefore, it is necessary to monitor how these changes affect AV acceptance.

6. Conclusions

The biggest roadblocks standing in the path of mass adoption of AVs may be psychological, not technological (Shariff et al., 2017). Understanding what factors and how they affect people's acceptance and adoption of AVs is critical. Relying heavily on online- or paper-based surveys and on participants with little or no experience of AVs in assessing public acceptance has been criticized. The present field study serves to understand the influences of direct experience on the magnitude of AV acceptance and its determinants and also on their associations, and to find what determinants can explain and predict AV acceptance. The field experiment invited 300 students, who would be the early adopters of AVs in visible future, to experience the nine complex scenarios in automated driving. Their direct experience of AV is found to increase their trust and two cognitive beliefs (perceived usefulness and perceived ease of use) related to SDVs, and it particularly led these two cognitive beliefs to be more predictive of behavioral intention to use SDVs. Perceived usefulness, trust, and perceived safety were positive predictors of participants' intention to use SDVs and willingness to re-ride in our AV. The AV experience enabled participants' perceived ease of use predict their behavioral intention. Trust imparted a direct effect, as well as an indirect effect, on AV acceptance. The present findings offer useful insight into designing and promoting AVs.

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