Social Trust and Risk Perception Towards Acceptance of Fully Automated Driverless Cars

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ABSTRACT

One of the most significant technological advancements in the transportation sector recently is the development of fully automated driving (FAD) cars. It offers several advantages for both individuals and companies. It may be less expensive, safer, and time-saving. We need to comprehend how people perceive and why they accept or reject FAD vehicle technology to predict and increase its acceptance. We investigated a technology acceptance model to account for the adoption of fully AD (FAD) cars, drawing on the trust heuristic and Technology Acceptance Model (TAM). According to this heuristic, perceived ease of use may indirectly influence acceptance by influencing social trust. Contrarily, perceived risk had no discernible impact on behavior-related intention to adopt FAD. The study confirmed the results using a survey (N = 200) and testing using structural equation modeling (partial least squares method). The implications of the findings for practitioners and academicians are further discussed in the study.

Keywords: Fully automated driverless vehicles, Technology acceptance model, social trust, perceived risk, Autonomous cars

1. INTRODUCTION

Vehicles that can sense their surroundings and navigate independently without human input are stated as automated vehicles (AVs). From Level 0 (no automation) to Level 5 (complete automation), the Society of Automotive Engineers (SAE, 2018) defines six degrees of AVs. A Level 5 automated vehicle is fully automated and is fitted with monitoring systems that enable it to monitor the driving environment and drive independently. Though AVs have a good number of advantages, firstly, they will reduce traffic congestion and fuel emissions due to automated and planned travel of the vehicles (Fagnant & Kockelman, 2015); secondly, the accidents will reduce since it has been found that 95% of road accidents happen due to human-error (Financial Express, 2020)and thirdly, it would be a boon for all those who cannot drive due to health issues or are indifferent to driving tests and processes(Duncan et al., 2015).

Moreover, since few nations have already authorized the use of AVs, it has started to pick up as a trend globally, though not popular enough to be called an accepted technology. Furthermore, with a large number of developing nations where the income, education and living standards are low, the understanding, use and acceptance of such a technology will have its issues.

The AVs promise energy efficiency, safety, lesser pollution, and enhanced

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mobility, but these benefits will impact the world around us only when the market widely adopts AVs. Recent studies have found that people's willingness to adopt autonomous vehicles is low (Abraham et al., 2017; Menon et al., 2016). The main reason for the low penetration of AVs around the globe is primarily due to their low acceptance amongst people, even for Level 3 AVs (Xu et al., 2018; Noy et al., 2018; Liu et al., 2018). Various recent studies have delved into the reasons leading to the acceptance of AVs in various countries. Various factors such as gender, i.e., males have more inclination towards AVs (Menon et al., 2016; Bansal et al., 2016), income groups (Bansal et al., 2016), people who are more technology-inclined (Bansal et al., 2016) and those living in urban areas (Shabanpour et al., 2018).

In India, the highest level of AV available for the public is mostly Level 2 automation. Companies like Tesla, Mercedes and Kia are trying to bring the next level of automation into Indian cars, but that is in the near future. Hence, a level 5 automation for most people in India and globally might be like a far thought, but that is not the case. Already companies like Alphabet have designed level 4 AV, and businesses like Waymo (taxi) have a fleet of level 4 taxis (Bogna, 2022). Hence, businesses are strongly inclined to shift and invest in higher levels of vehicle automation. In the present scenario, it becomes essential to understand the factors influencing the customers in choosing such AVs as their mode of transport and how businesses can make their marketing communication appropriate to build a positive image towards the technology. Various research in the past has tried to find out factors influencing the acceptance of AVs, but they do not address the psychological aspects of adoption like Initial trust (Xu et al., 2018; Talebian & Mishra, 2018; Abraham et al., 2017; Nordhoff et al., 2016). Thus, it becomes critically important to identify and evaluate the psychological factors such as initial trust towards AVs, safety and privacy risks.

The study proposes a theoretical model for AV acceptability. Given that Level 5 AVs may not be readily available for a while. However, businesses are investing millions of dollars in constructing them, and we explicitly focused on the acceptability of such vehicles. Companies must ascertain whether their investments are being made in the proper direction. Initial trust, Social Influence and perceived risk were added to the Technology Acceptance Model to create the model. This research is one of the first to evaluate Level-5 AV acceptability using the TAM, trust, perceived risk and social influence.

The results of this study could help us better understand how psychological characteristics like trust and social influence interact with other components of the technology acceptance model to determine how people embrace AV. From a practical standpoint, this study will assist marketers and policymakers in encouraging AV acceptability and decision-makers in the industry in attaining competitive advantages in the worldwide market.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS

The Technology Acceptance Model (TAM) has been one of the pioneering theories to identify factors influencing the adoption of technology (Davis, 1989; Davis et al., 1989); also Theory of Planned Behavior (TPB) was used by many researchers to study human behavior in general (Ajzen, 1991), but it was only the advent of Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and UTAUT2 which used human behavior to explain user acceptance (Venkatesh et al., 2012). These models fundamentally build upon the understanding that the perceptions and beliefs of an individual will affect their intentions, which will finally transfer into their actual actions. The two determinants of behavioral intention (BI) in TAM are perceived usefulness (PU) and perceived ease of use (PEOU). The UTAUT brings forth a favorable influence on performance expectancy (same as PU), effort expectancy (same as PEOU) and social influence on BI, which has a favorable influence on actual behavior along with the influence of facilitating condition. Additionally, according to UTAUT, the age, gender, experience of the technology, and voluntariness to use the technology by the user can help to control the relationship between BI and its antecedents. Hedonistic motivation, price value, and habit are three more constructs in the updated UTAUT2 model.

Various research has used these models to propose an acceptance model for automation, called Automation Acceptance Model (AAM) (Ghazizadeh et al., 2012). TAM was modified to incorporate compatibility and trust, and the Automation Acceptance Model was developed (AAM). The authentic relationships of antecedents and intention from TAM are the same in AAM. However, the influence of trust and compatibility on attitude and BI can be seen through PEOU and PU. Additionally, trust has a direct influence on BI.

Further studies added trust and perceived risk to the TAM in order to forecast AV acceptance. The study suggested that all the components directly influence whereas trust will indirectly influence BI through Perception (Choi & Ji, 2015; Xu et al., 2018). All expected connections were verified except for the direct relationship between perceived risk and BI. As a result, more significant research should be put into figuring out how perceived risk affects AV acceptability—it proposed that the two elements that directly affect AV adoption are trust and performance expectancy. The study also hypothesized that privacy risk, security risk, and reliability are the antecedents of trust and would indirectly affect adoption via trust.

Two recent systematic reviews on the acceptance of autonomous cars were published (Jing et al., 2020; Nordhoff et al., 2016), but both contained research on user approval of shared and private autonomous passenger shuttles without making a distinction between them. It is arguable if people adopt AVs differently depending on whether they will use them privately or in a shared format. For instance, attitudes, performance expectancy, and subjective norms/social influence have been reported as significant positive predictors of intentions to use both private and shared AVs (Yuen et al., 2020; Kaye et al., 2020). Where as the intention to use shared AVs were influenced by other factors such as the service of providing a shuttle (Nordhoff et al., 2016), the comfort of the ride, and service frequency (Chee et al., 2020). Although similar factors are observed, which can help in predicting users' intention to adopt both private and shared vehicles, perceived usefulness was observed to be a better predictor to view this difference in adoption (Motamedi et al., 2020).

2.1 Behavioral Intention and Use Behaviour

The considerable influence of behavioral intention toward using technology has been documented in several earlier research on technology adoption (Venkatesh et al., 2016, 2012; Ajzen, 1991). The study of behavioral intention (BI) is based on research in social psychology that identifies factors that influence BI (Wedlock & Trahan, 2019). The intention to employ technology is impacted by BI both directly and indirectly. Thus, hypothesizing,

H1: Behavioural intention has a positive influence on Use Behaviour

2.2 Perceived Ease of Use and Perceived Usefulness

The two critical variables in TAM are PU and PEOU (Davis, 1989). PU is “the degree to which a person believes that using a particular system would enhance his or her job performance” (p. 320). The meaning of PU is very close to UTAUT’s performance expectancy (Venkatesh et al., 2003). (Davis, 1989) defined PEOU as "the degree to which a person believes that using a particular system would be free of effort" and can be considered very similar to UTAUT’s Effort expectancy (Venkatesh et al., 2003). A large number of research in the past has established the effect of PE and PEOU on the acceptance of technology in various technologies (Ghazizadeh et al., 2012; Venkatesh et al., 2003; Davis, 1989)such as augmented reality in learning (Jang et al., 2021), facial recognition payment (Zhong et al., 2021), electric vehicles (Shanmugavel & Micheal, 2022) and of course AV adoption (Yuen et al., 2020). Thus, proposing the hypotheses:

H2: Perceived ease of use has a positive influence on Behavioural Intention

H3: Perceived ease of use has a positive influence on Perceived Usefulness

H4: Perceived Usefulness has a positive influence on Behavioural Intention

2.3 Perceived Usefulness and Perceived Risk

When consumers perceive technology to be risky, the usefulness, usability and behavioral control of the technology reduce for them. Users' attitudes and behavioral intentions to utilize fully automated driverless vehicles might be influenced by how they perceive risk and trust. As perceived risk increases, the strength of variables in TAM should generally decrease. Each of these hypotheses also affects the propensity to take risks, affecting the intention to use technologies.

H5: Perceived Risk has a negative influenceon Perceived usefulness

2.4 Perceived Ease of Use and Social Trust

Research in the past has found that consumers are more inclined to try out utilizing social networking for transactions if they view the activity involving social technology as having a lower risk or greater level of trust (Hansen et al., 2018). The results in online shopping (Ha & Stoel, 2009) and online communities (Posey et al., 2010) are consistent with the assumption that trust promotes self-disclosure online. In this context, positively perceived risk is correlated with usability, usefulness, and behavioral control, based on the rationale that consumers believe that security protocols and functions reduce risk in technologies by making them more challenging to use, less valuable, and less in their control. Thus, hypothesizing,

H6: Social Trust has a positive influence on Perceived Ease of Use

2.5 Social Trust and Perceived Risk

In order to overcome risk perceptions, trust is crucial (McKnight et al., 2002). Trust can assure the trustor that the trustee will be able to accomplish their goals, act in accordance with their promises, and care for them. It may increase the likelihood that the trustor will receive the benefits they are hoping for from the trustee. Social trust has already been shown to reduce risk perceptions and increase benefit perceptions (Siegrist & Cvetkovich, 2000). Social trust can enable people to overcome risk perceptions and believe in the manufacturers' promises about the advantages of fully automated driverless vehicles. It may also be supplemented by the people's faith in their government bodies or vehicle manufacturers.

H7: Social Trust has a negative influence on Perceived Risk

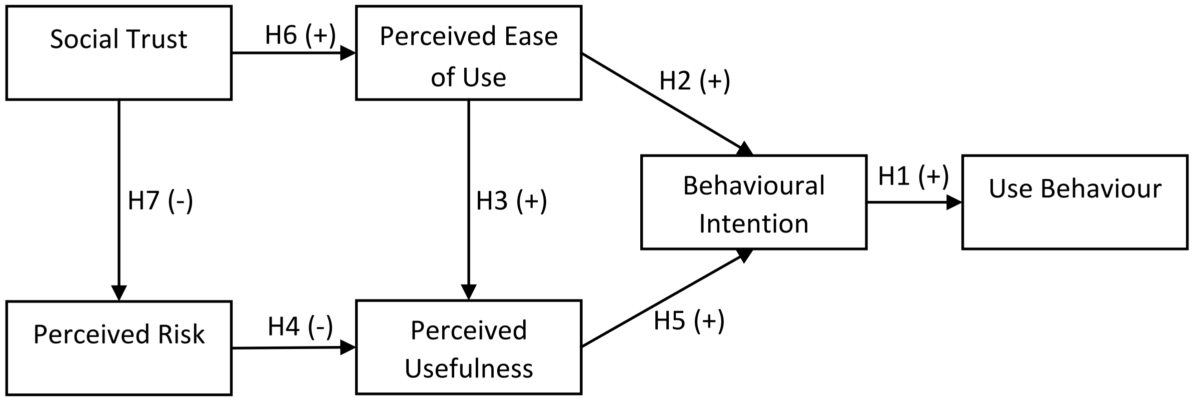

Fig. 1: Hypothesized Model

3. RESULTS AND ANALYSIS

The extended TAM model was tested using the Structural Equation Modelling using the Partial Least Square method. A fully functional trial of Smart PLS version 4 was used to run PLS-SEM. The most significant advantages of PLS-SEM are that it can replace CB-SEM since it can assist in avoiding issues associated with limited sample sizes. PLS-SEM can also estimate extremely complicated models and handle many latent variables. Finally, PLS-SEM can handle both reflecting and formative measurement models since its distribution assumptions for the variable and error terms are less strict (Henseler et al., 2009).

This research first assesses the measurement model and then the measurement of the structural model (Hair et al., 2017). The structural model helps to explain the relationships between the constructs in the model, where as the measurement model describes how each construct is measured. PLS-SEM has the advantage that it can simultaneously analyze the measurement and structural model, improving estimation accuracy (Barclay et al., 1995).

3.1 Respondents' Characteristics

The survey was shared through online questionnaire design software. The questionnaire was shared with 320 respondents, out of which 225 responses were received, which provided us with 200 filled responses upon cleaning and removing partial entries. The demographic of the survey respondents come from Metro cities in India and consider only those who are car owners or car enthusiasts. 28.5 percent of respondents were women, and 71.5 percent were men, according to their gender. The respondents ranged in age from 14 to 50, but 93.5 percent were within the 18 to 35 age bracket, which is also the demographic where people are most receptive to new ideas and have the means to spend. Table 1 provides a summary of the above information.

Table 1: Demographic Information

Gender / Age	18-25yrs	25-35yrs	35-45yrs	45-60yrs	Grand Total
Male	95	41	6	1	143
Female	39	13	2	3	57
Grand Total	134	54	8	4	200

The external model evaluation is first carried out to ensure that appropriate metrics are included in the model and that they appropriately support the theoretical components. The measurement model was used to evaluate the convergent and discriminant validity, whereasCronbach's alpha and composite reliability were used to assess reliability. The internal consistency reliability of the model was verified by observing that the Cronbach alpha is between 0.814 to 0.917.The values of 0.80 and above are considered valid for Cronbach's alpha.

The indicator loadings are analyzed to evaluate the reflective measurement model. The average variance extracted from the constructs (AVE) for all items was used to assess the convergent validity. If the construct can account for at least 50% of the variance (i.e., AVE of more than 0.50 or above) in the items, it can be deemed acceptable. Any loading above 0.50 is recommended since the construct can account for at least 50% of the variance in the indicators.

Table 2: Measurement Model

Constructs	Items	Loadings for each factor	Variance Inflation Factor	Composite Reliability	Cronbach's Alpha	AVE (Avg. Variance Extracted)
PEOU	PEOU_1	0.704	1.336	0.835	0.739	0.559
	PEOU_2	0.742	1.551			
	PEOU_3	0.736	1.455			
	PEOU_4	0.805	1.454			
PU	PU_1	0.894	2.967	0.918	0.881	0.736
	PU_2	0.861	2.836			
	PU_3	0.870	2.521			
	PU_4	0.805	1.659			
ST	ST_1	0.775	1.417	0.849	0.733	0.652
	ST_2	0.813	1.414			
	ST_3	0.833	1.558			
PR	PR_1	0.341	1.299	0.714	0.716	0.565
	PR_2	0.468	1.609			
	PR_3	0.348	1.406			
	PR_4	0.832	1.239			
	PR_5	0.824	1.365			
BI	BI_1	0.832	1.868	0.867	0.769	0.685
	BI_2	0.869	1.990			
	BI_3	0.778	1.333			
UB	UB_1	0.801	1.868	0.861	0.785	0.608
	UB_2	0.766	1.990			
	UB_3	0.810	1.333			
	UB_4	0.739	1.496			

The result also evaluates internal consistency reliability by utilizing composite reliability (Joreskog, 1971). In exploratory research, reliability levels lying within 0.60 & 0.70 are deemed "acceptable," whereas values within 0.70 & 0.90 are deemed "satisfying to good." Values of composite dependability of more than 0.95 are seen as troublesome since they suggest item redundancy (Diamantopoulos et al., 2012). All the constructs' average variance extracted is more than 0.6, and composite reliability values are higher than 0.70, suggesting high reliability.

Table 3: HTMT (Heterotrait-Monotrait Ratio)

	BI	PEOU	PR	PU	ST
BI					
PEOU	0.801				
PR	0.198	0.249			
PU	0.594	0.557	0.263		
ST	0.497	0.609	0.309	0.335	
UB	0.640	0.726	0.215	0.526	0.411

3.2 Structural Model Assessment

Researchers can describe the link between the latent constructs by evaluating the structural model (Hair et al., 2017). Figure 2 shows the structural model with the newly included constructs, along with every path coefficient and p-value. The structural model is assessed using the coefficient of determination (R^2) and the analysis of the path coefficients. The results of the hypothesis testing are displayed in Table 4. R^2 is equal to 0.44 for behavioral intention and 0.254 for user behavior. Thus, this model can predict only 44 percent of the variation in behavioral intention and 25.4 percent of the variance in use behavior toward autonomous cars in India. According to (Zikmund et al., 2013) (p. 513), such R-squared values often indicate effects with a moderate to small magnitude. Human behavior is generally difficult to predict, primarily when it is based on an incomplete grasp of new technology. However, a significant relationship between all of the hypothesized factors was discovered.

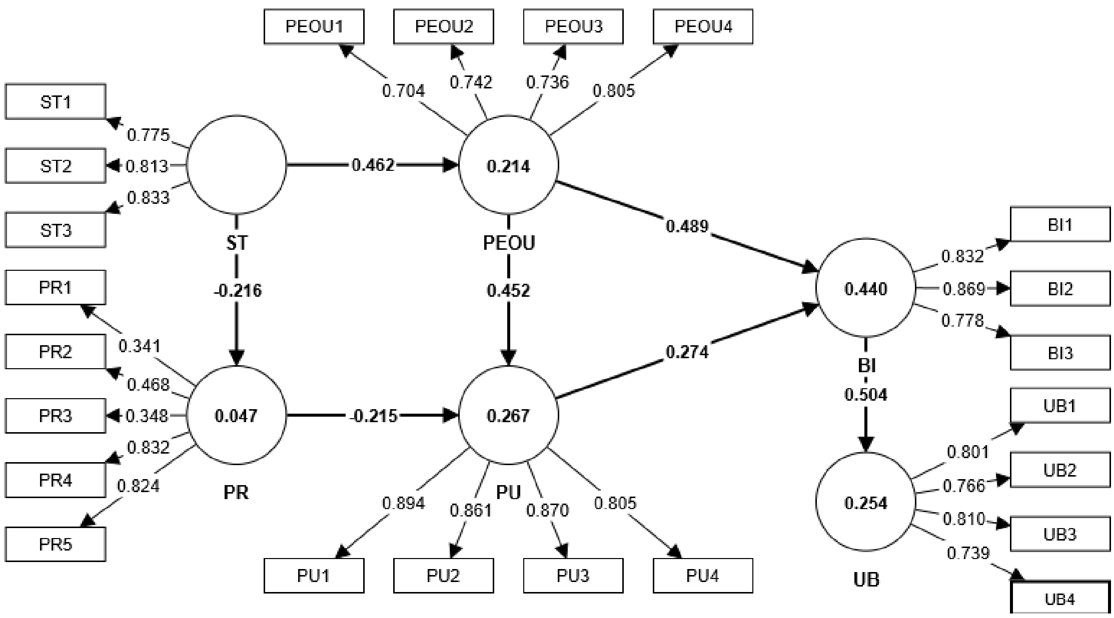

Fig. 2: Path Diagram (Smart PLS 4.0)

Table 4: Summary of Hypothesis

Hypothesis	Relation	Beta	T-value	p-value	Decision
H1	BI → UB	0.504	9.882	0.000	Supported
H2	PEOU → BI	0.489	9.537	0.000	Supported
H3	PEOU → PU	0.452	6.729	0.000	Supported
H4	PR → PU	-0.215	0.879	0.379	Not Supported
H5	PU → BI	0.274	4.813	0.000	Supported
H6	ST → PEOU	0.462	7.906	0.000	Supported
H7	ST → PR	-0.216	1.780	0.075	Not Supported

4. CONCLUSION AND DISCUSSION

This research was conducted to observe the influence of social trust and risk in adopting autonomous vehicles using TAM and trust theory at this very early stage. The study's main objective was to identify the primary determinants influencing behavioral intention and, finally, the Use behavior of Automated Vehicles in India. The study also introduced two critical antecedents to the TAM model namely Social Trust and Perceived Risk, thus intending to find their significance towards the acceptance of automated driverless vehicles. The identified constructs, namely Social Trust, Perceived Risk, Perceived Ease of Use, and Perceived Usefulness, significantly influenced behavioral intention. All the relationships framed in the research are positive except between Social Trust, Perceived Risk, and Perceived Usefulness. This implies that any increase in those primary constructs (PU, PEOU) will positively influence behavioral intention or Use behavior towards fully automated driverless vehicles. Though an increase in the social trust will reduce the perceived risk, an increment in perceived risk will reduce the perceived usefulness of the technology for the user.

This study found all three primary constructs borrowed from TAM to be significant (Davis, 1989). Perceived Ease of Use had a more substantial influence on behavioral intention than Perceived Usefulness, probably since a technology where the driver would have to interact with the car as minimum as possible may increase anxiety. Thus, consumers may consider the technology to be more advanced and challenging to use. The newly added constructs of Social Trust and Perceived Risk also significantly influenced the TAM constructs, thus influencing BI and UB. Users, due to the unavailability of complete information regarding a fully automated driverless vehicle, may consider it risky and let their lives be at stake under a machine's trust.

Social trust is a variable that indirectly affects the intention and use of fully automated driverless vehicles, which is well validated by past research (Bronfman & Vázquez, 2011). Social trust's direct influence is considered to build acceptance through the affective path, while its indirect effect is considered to build acceptance through the cognitive path (Terpstra, 2011; Terwel et al., 2009; Midden & Huijts, 2009). Thus, we conclude that social trust indirectly affects the intention to adopt through a cognitive route.

4.1 Managerial Implications

Acceptance of fully automated driverless vehicles in India will be firmly by trust and perceived risk by end consumers. More than having advanced features and further technological progress is needed to ensure the adoption of driverless cars. The study suggests to practitioners how to build social trust amongst consumers for faster adoption of fully automated driverless vehicles. Past research has suggested that social trust may lead to the adoption of automated driverless vehicles (Noy et al., 2018; Abraham et al., 2017) but does not precisely point to the adoption's cognitive aspect. Thus, manufacturers should provide enough cognitive psychological cues to their target customers to build social trust.

Consumers consider perceived risk as a factor that is of concern to them. Automated vehicles' primary attraction is their ability to reduce accidents and travel safety (Fagnant & Kockelman, 2015). Though, the effect size of risk perception on acceptance of fully automated driverless vehicles is found to be small. The consumers may be unable to see beyond into the future about the unknown risk. Thus, risk had an insignificant effect on acceptance. However, historically, we have seen hindrances in technology acceptance and use due to risk concerns associated with technology, such as fusion power reactors. Thus, the manufacturers should immediately start communications to reduce the risk perception.

4.2 Future Research Directions

Though the study tried to address various aspects affecting the adoption of fully automated driverless vehicles and suggest an extended social trust integrated with the TAM model, it did not identify the factors leading to social trust creation. Further research on antecedents of social trust leading to acceptance may give practitioners a clearer view of what to communicate to create solid communication with its target consumer. The study is also limited to a small convenience sample of responses and cannot be generalized to all countries. Past research has shown the different factors leading to the acceptance of automated vehicles in different countries (Guan et al., 2021; Costantini et al., 2020; Kyriakidis et al., 2019).

The analysis of the UTAUT and its further extensions done in more recent research reveals a demand for using variables such as age, gender, and former experience in information technology as moderating variables to understand the influences of social and demographic changes on the acceptance of new technology could not delve into few areas like comparing adoption factors in various emerging nations or a comparison of emerging nations vis-a-vis developed nation which could be a good work for future research. Also, this study was conducted only in a single nation and thus cannot be fully generalized. Thus, further expansion across other countries can help generalize the study and attract cultural dimension as a moderating variable that might influence behavioral intention. How citizens of a developed country might accept such new technology might vary from how citizens of a developing nation might do so; thus, a comparative study between users of developed and developing nations can also be an interesting perspective to develop. The study also addressed only end consumers (individuals) as the study population. In contrast, the scope to take it further for the adoption of automated vehicles for businesses/ organizational use could add additional theoretical and practical value.

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