Early bird catches the worm!
Meta-analysis of autonomous vehicles adoption - Moderating role of automation level, ownership and culture

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Abstract

The ongoing competition between traditional vehicle manufacturers and technology companies for quickly developing autonomous vehicles (AVs) and gaining early traction in the market is well known. However, some issues need to be cleared regarding the antecedents of the behavioral intention to use AVs. In this context, we conducted a meta-analysis using the TIS (Technological, Individual, and Security) framework, to understand the convergence and divergence of the factors influencing the behavioural intention to use AV technology. This meta-analysis tested the hypotheses using a database of 65 studies obtained from 58 articles with the cumulative sample size of 37,076. The study identified perceived usefulness, attitude, trust, safety, hedonic motivation, and social influence as the critical antecedents of AV adoption. Several of the relationships investigated in the study were moderated by factors such as level of automation, vehicle ownership and culture. The results revealed fewer incentives for the public to accept AVs. Theoretical contributions and recommendations to practitioners and policymakers have also been discussed.

Keywords – Autonomous vehicles, Behavioral intention, Technology adoption, Meta-analysis.

1. Introduction

Autonomous vehicles (AVs), which are an integral part of an intelligent transport system, would significantly alter mobility and revolutionize the future of driving. Depending on the level of automation (SAE, 2016), AVs are capable of performing all the driving functions, either without or with a little support from the human operator. When the driver sets the destination for the trip, a fully autonomous AV can automatically identify the possible routes, select the best course, navigate or drive passengers to the destination, and park the vehicle (Du et al., 2021). The development of AVs is driven by advancements in transport technologies such as autonomous cruise control, intelligent speed assistance, autonomous braking systems, and lane-keeping assist systems. It is powered by developments in information and communication technologies such as advanced sensors, LiDAR, radar, navigation technologies (GPS), computer vision, real-time data processing and sophisticated machine learning algorithms (Lee et al., 2019b).

Even with the commercialization of AVs in the near future (Zhu et al., 2020), diffusion of autonomous vehicle technology is expected to be rather slow. The AAA Survey (2021) revealed that 86% of American drivers are afraid of riding fully autonomous self-driving vehicles. On the positive side, the survey indicated that close to 60% of the participants are ready to consider self-driving vehicles as an alternative to public transportation. Recent market research by Statista

(2021) predicted that by 2030 AVs would account for 12% of the vehicle registrations worldwide. Further, Litman (2021) postulated that affordable AVs will be commonly available between 2040 and 2060. Growth in AVs is expected to be fueled by private ownership (Montoro et al., 2019).

AVs represent a disruptive technology that has garnered widespread attention among vehicle manufacturers, researchers, and policymakers, even before its commercial launch. The global market size for self-driving cars is expected to reach $37 billion by 2023 (Satista, 2019). Traditional vehicle manufacturers such as BMW, Toyota, Volvo, Hyundai, emerging automobile manufacturers such as Tesla and Uber, and technology giants such as Waymo (Google) and Apple are making substantial investments in developing AVs to garner early traction in the market. According to the AV readiness index published by KPMG (2020), policymakers from different jurisdictions are enacting changes in "legislation, technology, and infrastructure" to facilitate consumer acceptance. Research on AVs has focused on technological capability, safety aspects, and the potential users' behavioral intention to adopt the AV technology (Jing et al., 2020; Faisal et al., 2019; Martínez-Díaz & Soriguera, 2018).

Over the last few years, there has been a surge in empirical investigations focusing on the predictors of AV adoption. There is significant validation in the literature for technology adoption, as well as for psychological and behavioral theories in the context of AV adoption. Although the existing literature has extended our understanding of the emerging phenomena, there exist four limitations that merit scholarly attention.

Firstly, extant studies reported inconsistent findings for some of the key relationships that examined the adoption intention of AVs. For instance, while perceived ease of use was marked as a significant predictor of adoption intention by some (Zhang et al., 2020; Liu et al., 2020), others opined that it is non-significant (Jing et al., 2021; Hegner et al., 2019). Further, Kapser & Abdelrahman (2020) and Madigan et al. (2017) found facilitating condition as significant predictor of behavioral intention to use AVs, whereas Kaye et al. (2020) and Nordhoff et al. (2020a) found this relationship as non-significant. Mixed findings reported in the literature inhibit us from drawing generalized conclusions on the impact of the antecedents on the intention to adopt AVs. Therefore, one of the main objectives of the present study is to reconcile the conflicting results in the meta-analysis and infuse generalizability among the antecedents of intention to adopt AVs.

Secondly, there is enormous variation in the relationships investigated for AV adoption. For example, the relationship between perceived usefulness and behavioral intention is consistently found to be significant. However, the impact size of the relationship varied between -0.07 (Herrenkind, et al., 2019b) to 0.74 (Baccarella et al., 2020). Similarly, the relationship between perceived ease of use and perceived usefulness varied from 0.02 to 0.88. These variations make the explanatory power of the relationships questionable. Bornholt & Heidt (2020) conducted a qualitative review of AV adoption. They called for a meta-analytic study to investigate the combined effect size and the explanatory power of the relationships. Thus, the present study attempts to establish the combined effect size for the dominant relationships.

Thirdly, studies have deployed technology adoption theories such as the Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate AV adoption. Moreover, the explanatory power of these theories has widely varied. For example, the UTAUT model deployed by Nordhoff et al. (2020a) accounted for 87.7% of the variance in behavioral intention to use AVs. In contrast, a study conducted by Feys et al. (2020) explained only 20% of the variance. Through meta-analysis, we investigated the dominant relationships that correspond to leading theories on technology acceptance. A synthesis of the theoretical models will enable the scholars to understand the applicability and relevance of these AV adoption theories and guide future studies.

Finally, the moderating impact of contextual factors is lacking in the literature. Individual studies have considered the adoption of different levels of automation, i.e., Level 3 - conditional automation (Zhang et al., 2020; Buckley et al., 2018), Level 4 - high automation (Kaye et al., 2020; Madigan et al., 2017), and Level 5 - full automation (Zhu et al., 2020; Nastjuk et al., 2020). Public opinion surveys revealed varied perspectives on the consumers' preference for the higher levels of automation. A public opinion survey conducted by Schoettle & Sivak (2014) revealed that the increasing levels of automation reduce the intention to accept. Conversely, Abraham et al. (2017) argued that the tendency of males to adopt AVs increases with the higher levels of automation. Thus, the impact of increasing levels of automation on the AV adoption is inconclusive. To fill this gap, the present study investigates the moderating impact of the level of automation on AV adoption. Vehicle ownership, which could be a critical factor in the adoption of AVs, has received scant attention in the literature (Mohammadzadeh, 2021). Diffusion of AV technology to masses through public transportation is paramount to the very success of AVs. Thus, the present study investigates the moderating impact of vehicle ownership (Public vs. Private).

Information systems literature has established that behavioral relationships may not hold good across different cultures (Srite & Karahanna, 2006). Different variables exert differing levels of influence on diverse cultural settings. Availability of technology and the resources needed to consume the technology could vary between the cultures. Understanding the cultural differences is essential for the organizations to device strategies for different markets. Numerous studies (Jing et al., 2021; Nastjuk et al., 2020; Kaye et al., 2020; Wang et al., 2020; Karnouskos, 2020a) have highlighted the imperative to understand the cultural differences for the successful diffusion of AVs. Kaye et al. (2020) investigated the adoption of autonomous cars in Australia, Sweden, and France and posited that culture significantly influences the acceptance of AV technology. However, studies examining these cultural differences are currently lacking in the literature. More specifically, Leicht et al. (2018) called for the future AV adoption studies to investigate the moderating impact of culture.

Therefore, the present study investigates the moderating impact of culture on the adoption of AV technology. This meta-analysis considers the cultural differences across eastern and western regions for the following reasons. First, extant research revealed that technology adoption behaviors differ between eastern and western cultures (Zhang et al., 2012). Second, prior literature indicated that cultural dimensions (i.e., individualism/collectivism, masculinity/femininity) exhibit similar patterns in eastern/western cultures (Anderson et al., 2010; Mehta et al., 2021). Thus, examining the cultural differences in eastern and western cultures would accommodate the cultural dimensions. Third, recent meta-analytical studies confirmed that technology adoption significantly differs across eastern and western cultures (Sarkar et al., 2020; Mehta et al., 2021; Gopinath et al., 2021). Finally, from the context of AVs, studies have indicated that adoption in highly motorized western cultures could be significantly different from that in the eastern cultures (Baig & Mir, 2020; Karnouskos, 2020a; Zhang et al., 2020; Wang et al., 2020).

The term meta-analysis refers "to the statistical analysis of large collection of analysis results from individual studies for the purpose of integrating the findings" (Glass, 1976). Meta-analysis in IS research has received significant attention in recent years (Jeyaraj, 2022b). Maturing IS disciplines and substantial traction from scholars to understand the facets of disruptive information technologies resulted in inconsistent findings. This has created the need for meta-analytical studies in IS research (Kepes & Thomas, 2018). Meta-analysis uses sets of statistical analyses to resolve inconsistencies by collating and synthesizing effect sizes (King & He, 2005). Other advantages of meta-analysis include accumulation of cumulative knowledge, generalizability of relationships, testing the applicability and usefulness of IS theories in understanding particular phenomena (Jeyaraj & Dwivedi, 2020). For these reasons, the present study uses meta-analysis to synthesize key relationships governing AV adoption.

In sum, the objective of the study was threefold: (1) Developing a holistic conceptual model for the adoption of AVs using the TIS (technical, individual, and security factors) framework, (2) Conducting a meta-analysis to validate the conceptual model and establish the significance and the strength (combined effect size) of the relationships investigated, (3) Understanding the potential moderating impact of the level of automation, vehicle ownership and culture.

The remainder of the study is organized as follows: Section 2 describes the literature review, conceptual model, and hypothesis development; Section 3 explains the data collection, research method, and analysis procedures used; Section 4 presents the result of the meta-analysis; Section 5 discusses the key results, presents the theoretical and practical contributions of the study, and describes the study limitation and future scope, and Section 6 contains the conclusion.

2. Theoretical Background

AVs have fascinated researchers even before their commercial availability due to the disruptive nature of the technological innovation. Adoption of AVs is crucial for human society to realize the full potential and the benefits that AVs promise (Du et al., 2021). Extant studies on AV adoption are broadly classified into two types - public opinion surveys and theory-based surveys. Public opinion surveys analyzed the consumers' willingness to use AVs (Hulse et al., 2018; Bansal et al., 2016), and presented their findings as descriptive statistics, which depicted the relationship between demographic variables (i.e., age, gender, and income) and willingness to use AVs. The second type of studies employed a variety of behavioral theories, such as the Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), Social Cognitive Theory (SCT), Unified Theory of Acceptance and Use of Technologies (UTAUT), and the Innovation Diffusion Theory (IDT) to understand the factors influencing behavioral intention to accept AVs.

TPB postulates that three psychological beliefs, namely attitude (behavior belief), subjective norm (normative belief), and perceived behavioral control (control belief) predict the intention to perform target behavior (Ajzen, 1991). Many studies have successfully validated the applicability of TPB in understanding the adoption of AVs (Dai et al., 2021; Kaye et al., 2020; Buckley et al., 2018; Yuen et al., 2020c). Kaye et al.(2020) investigated the intention to use automated cars in Australia, France, and Sweden, and explained 58 to 74% of the variance. Studies have indicated that the extended TPB can explain as high as 87% of the variance in the intention to use shared autonomous vehicles (Yuen et al., 2020c).

TAM is a widely popular information systems adoption model, and has been extensively used to explore the adoption of diverse technologies. TAM proposes perceived usefulness and perceived ease of use as antecedents of attitude and technology acceptance (Davis et al., 1989). TAM is the widely used framework to understand the adoption intention of AVs. Several studies have investigated the impact of perceived usefulness, perceived ease of use, and attitude on the behavioral intention to accept AVs (Jing et al., 2021; Man et al., 2020; Nastjuk et al., 2020; Zhang et al., 2019; Herrenkind et al., 2019b; Choi & Ji, 2015). Buckley et al. (2018) found that TAM construct perceived usefulness alone account for 41% of the variance in AV adoption intention. Several studies have adopted the extended TAM for investigating AV adoption (Jing et al., 2021; Chen, 2019; Hegner et al., 2019). In the extended TAM model, core TAM constructs have been expanded with additional context-specific and external constructs. Further, Lee et al. (2019a) revealed that when TAM is extended with the context-specific factors (i.e., psychological ownership, relative advantage) it explained 76% of the variance in the intention to use AVs.

UTAUT is another robust framework widely used in the technology adoption literature. Venkatesh et al. (2003) collated and synthesized eight theoretical models to develop this unified framework. UTAUT proposed four independent constructs to predict behavioral intention: performance expectancy, effort expectancy, facilitating condition, and social influence. The constructs' performance expectancy and effort expectancy resembles the TAM construct's perceived usefulness and ease of use, respectively (Dwivedi et al., 2011). Venkatesh et al. (2012) furthered the UTAUT model with UTAUT2 by incorporating three additional constructs: hedonic motivation, price value, and habit. Several studies have deployed the UTAUT framework to investigate the intention to adopt AVs (Nordhoff et al., 2020a; Erskine et al., 2020; Kapser & Abdelrahman, 2020; Feys et al., 2020; Madigan et al., 2016). Erskine et al. (2020) investigated the consumer acceptance of fully autonomous AVs and found that four core constructs of UTAUT could explain 75.7% of the variances in behavioral intention. On the other hand, Nordhoff et al. (2020a) found 87.7% of the variances in the behavioral intention to use AV by deploying UTAUT2.

In addition to constructs from behavioral theories, studies have employed the context-specific and external constructs that could play a vital role in the diffusion of AVs in the market. Consumers' trust in reliable and safer execution of AVs is paramount to the adoption. Numerous studies have investigated the impact of trust in AV adoption (Du et al., 2021; Zhang et al., 2020; Yuen et al., 2020d; Buckley et al., 2018). Perceived risk (Zhu et al., 2020), perceived benefit (Manfreda et al., 2021), and perceived safety (Sener et al., 2019) are the other dominant variables studied in AV adoption.

Information system research has shown that the espoused culture has a significant influence on technology adoption (Srite & Karahanna, 2006; McCoy et al., 2005). Culture refers to "the collective programming of the mind which distinguishes the members of one human group from another" (Hofstede, 2001). Shared knowledge and beliefs about the systems, processes and technology emanates from the socialization process, and is expected to drive attitude, interactions and behaviors of the individuals (Triana et al., 2021). Further, varying availability of resources, technology, and supporting infrastructure in different cultures also influences the technology adoption and diffusion.

Hofstede's cultural framework is the commonly used theoretical foundation for understanding the cross-cultural influences (Hofstede, 2001). Four dimensions of espoused national culture - individualism vs. collectivism, masculinity vs. femininity (relates to the cultural characteristics, not to be confused with gender), power distance, and uncertainty avoidance have been the guiding posts for exploring the cultural impact on technology acceptance (Vos & Boonstra, 2022; Srite & Karahanna, 2006). Meta-analysis is a useful technique to elicit the cultural differences using sub-group analysis. Some of the recently published meta-analysis studies have established that antecedents of behavioral intention (Jadil et al., 2021; Mehta et al., 2021) significantly differs between eastern and western cultures.

Recently, few systematic literature reviews have analyzed the adoption of AVs. Jing et al. (2020) synthesized the determinants of AV adoption and found seven constructs from behavioral theory and six constructs from non-behavioral theory crucial for AV acceptance. Similarly, Alawadhi et al. (2020) extracted 14 constructs from the structured review and grouped them into four categories, i.e., technology, infrastructure, legal, and user acceptance. Golbabaei et al. (2020) qualitatively reviewed and identified ten psychological constructs, ten mobility-related constructs, and demographic variables based on prior studies of AV adoption. Further, they highlighted the assessment bias in the qualitative reviews. Bornholt & Heidt (2020) articulated the need for the meta-analysis study to investigate the explanatory power of the antecedents of AV adoption. Therefore, the present study conducted a meta-analysis to understand the cumulative impact of constructs based on the findings reported in the studies investigating the adoption and diffusion of AVs. This study also reconciled the existing inconsistencies to establish concrete evidence for the significance of the relationships that can guide future studies.

3. Conceptual Model and Hypothesis development

The study proposed a comprehensive conceptual model to facilitate cumulative understanding on the AV adoption (Fig. 1). The conceptual model was developed in three steps. The first step involved the identification of key constructs based on the frequency of usage in AV adoption literature and their significance to the adoption and diffusion of AVs. In the second step, we synthesized the theoretical constructs drawn from several technology acceptance theories, and grouped constructs with similar meanings. For instance, perceived usefulness from TAM and performance expectancy from UTAUT share similar meanings (Dwivedi et al., 2011; Zhao et al., 2018). Thus, perceived usefulness is grouped with performance expectancy. Further, perceived ease of use from TAM is similar to the effort expectancy from UTAUT (Dwivedi et al., 2011). Thus, perceived ease of use is grouped with effort expectancy. Social influence from UTAUT and subjective norm from TPB share similar imports (Zhao et al., 2018). Thus, the construct of social influence is grouped with subjective norm. By doing so, the conceptual model accounts for all the core constructs from TAM, UTAUT and TPB models, either directly or indirectly.

Finally, the selected variables were crystalized into the technological, individual, and security dimensions of AVs. Technological dimension included perceived usefulness, perceived ease of use, facilitating conditions, and social influence (Dwivedi et al., 2011; Kim and Ho, 2021; Khakurel et al., 2019). Individual differences or human factor comprised of attitude, hedonic motivation, perceived benefits, price evaluation, and perceived behavioral control (Patil et al., 2020; Tan et al., 2012). Security dimensions pertinent to the AV technologies included trust, perceived safety, and perceived risk (Manfreda et al., 2021; Flowerday & von Solms, 2006). Furthermore, we have examined the level of automation, vehicle ownership and culture as moderators that are crucial for the wider diffusion and policy formulation concerning AV technology.

3.1. **Technology factors**

3.1.1 Perceived usefulness

Perceived usefulness refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis et al., 1989). The usefulness of the innovation stated by the companies and the usefulness perceived by the actual users could significantly differ (Gourville, 2006). Thus, it is essential to understand the usefulness perceived by the consumers. Numerous studies have established perceived usefulness as a significant predictor of behavioral intention (Jing et al., 2021; Yuen et al., 2020a; Baccarella et al., 2020; Zhu et al., 2020). Xu et al. (2018) and Panagiotopoulos & Dimitrakopoulos (2018) revealed perceived usefulness as the strongest predictor and the most important factor for AV adoption. Studies have posited that manufacturers should emphasize the utility of the AVs, such as enhanced safety (Liu et al., 2020), productivity improvement, energy savings (Baccarella et al., 2020), efficient parking space utilization, and other environmental benefits (Wu et al., 2019) to promote the usefulness of AVs. Prior research has consistently demonstrated the positive effect of perceived usefulness on behavioral intention. Thus, we put forward the following hypothesis:

H1a. Perceived usefulness has a positive effect on behavioral intention to use AVs.

TAM proposed perceived usefulness as a key determinant of attitude towards technology use. Davis et al. (1989) conceptualized that "positively valued outcomes often increase one's affect (attitude) towards the means to achieving those outcomes." Extant literature revealed perceived usefulness as a vital factor in understanding the attitude towards technologies such as augmented reality (Holdack et al., 2022), healthcare technologies (Holdack et al., 2022), and mobile commerce (Chi, 2018), among others. Utility and performance of vehicles are essential attributes of usefulness that could influence attitude toward AVs. In the AV context, several studies have consistently proven perceived usefulness as a significant predictor of attitude (Jing et al., 2021; (Nastjuk et al., 2020; Müller, 2019). Herrenkind et al. (2019b) postulated that a positive attitude would be generated when the individuals perceive AVs as a viable future transport. Further, Man et al. (2020) revealed that potential benefits of AVs, such as performance efficiency and fuel savings, would directly influence attitude. Thus, we put forward the following hypothesis:

H1b. Perceived usefulness has a positive effect on attitude towards AVs.

3.1.2 Perceived ease of use

Perceived ease of use refers to "the degree to which a person believes that using a particular system would be free of effort" (Davis et al., 1989). Perceived ease of use could directly affect behavioral intention (Venkatesh, 2000), or it could indirectly influence behavioral intention through perceived usefulness (Davis et al., 1989). However, the impact of perceived ease of use on behavioral intention has received mixed responses. Some studies argued perceived ease of use as a non-significant factor as the AVs do not require human intervention, and vehicle management is taken on its own (Jing et al., 2021; Lee et al., 2019a). Contrary to that, some studies have shown the significance of perceived ease of use in AV adoption (Herrenkind et al., 2019b; Chen, 2019; Yuen et al., 2020a). Xu et al. (2018) revealed that participants' experience with AVs made them realize the importance of perceived ease of use. To examine the divergent findings, we put forward the following hypothesis:

H2a. Perceived ease of use has a positive effect on the behavioral intention to use AVs.

Perceived ease of use is a vital construct in understanding the innovation diffusion process. Davis et al. (1989) proposed perceived ease of use as the antecedent of perceived usefulness. The potential benefits associated with the innovation trigger the individual to consider using them. However, complex innovations available today offer a myriad of benefits to the users. Herein, the degree of ease associated with the technology determines the perception of benefits from innovation adoption. Thus, perceived usefulness tends to increase with the perceived ease of use (Venkatesh & Davis, 2000). In the AV context, perceived ease of use has been consistently found as a significant predictor of perceived usefulness (Jing et al., 2021; Baccarella et al., 2020, Zhang et al., 2020). People who easily adopt AVs discover the usefulness of technology (Yuen et al., 2020a). Herrenkind et al. (2019b) revealed that the convenience and simplicity associated with the vehicles made individuals derive greater usefulness from AVs. Further, Wu et al. (2019) highlighted the need for wider deployment of facilities such as charging stations that can enhance the convenience for AV users. Thus, we put forward the following hypothesis:

H2b. Perceived ease of use has a positive effect on perceived usefulness.

TAM model hypothesized that perceived ease of use influences attitude towards technology use (Davis et al., 1989). When the users perceive AVs as easy to learn and operate, they tend to develop a positive attitude. Contrarily, the learning barrier and complexity of driving AVs negatively affect AV use. In the AV context, several studies have successfully validated the relationship between perceived ease of use and attitude (Herrenkind et al., 2019a; Nastjuk et al., 2020; Zhang et al., 2019). However, Man et al. (2020) found a non-significant impact of perceived ease of use on attitude. Yet, they have argued that perceived ease of use indirectly influences attitude mediated by perceived usefulness. Relationships involving ease of use are also affected by external variables. Herrenkind et al. (2019a) showed that perceived ease of use had a low impact on attitude towards public transport as the users are already familiarized with the design of shared vehicles. Chen (2019) revealed that perceived ease of use significantly affected the attitude of individuals aged above 40. To investigate the combined effect size, we put forward the following hypothesis:

H2c. Perceived ease of use has a positive effect on the attitude towards AVs.

3.1.3 Facilitating condition

Facilitating condition refers to "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003). Facilitating condition was not included in all the studies that have utilized the UTAUT to investigate AV adoption. Venkatesh et al. (2003) indicated that the construct facilitating condition would be more helpful in predicting the usage than intention. Some studies found a significant relationship between facilitating condition and behavioral intention (Kapser & Abdelrahman, 2020; Madigan et al., 2017). Developing capabilities such as allied infrastructure, human-machine interface, and vehicle communication protocols are essential for facilitating the smooth operation of AVs. Some studies have also revealed a non-significant relationship between facilitating condition and behavioral intention (Kaye et al., 2020; Nordhoff et al., 2020a). Lack of AV experience was stated as the reason for the non-significant relationship. Conflicting results obtained for the relationship between facilitating condition calls for further investigation. Thus, we put forward the following hypothesis:

H3. Facilitating condition has a positive effect on the behavioral intention to use AVs.

3.1.4 Social influence

Social influence refers to "the degree to which an individual perceives that it is important for others to believe that he or she should use the new system" (Venkatesh et al., 2003). Several studies have investigated the relationship between social influence and behavioral intention to use AVs. Findings from the studies have consistently established social influence as a significant predictor of behavioral intention (Zhang et al., 2020; Nordhoff et al., 2020a; Liu et al., 2020; Sener et al., 2019; Madigan et al., 2017). Opinions of the important social-circle members such as family, friends, colleagues, and peers were found to influence the adoption intention of AVs significantly. The car is perceived as a status symbol in the social environment and adds to the consistent support for the social influence construct (Panagiotopoulos & Dimitrakopoulos, 2018). Thus, we put forward the following hypothesis:

H4. Social influence has positive effect on behavioral intention to use AVs.

3.2 Individual differences

3.2.1 Attitude

Attitude refers to "an individual's positive or negative feelings in performing a target behavior" (Davis et al., 1989). In the context of AVs, "attitude" refers to "the internal evaluation of AVs which can be favorable or unfavorable" (Yuen et al., 2020d). Positive attitude towards AVs can be formed when users firmly believe in utility, feel, and value maximization in using AVs (Nastjuk et al., 2020). Prior studies have revealed that creating a positive attitude drives the behavioral intention to adopt AVs (Man et al., 2020; Sener et al., 2019). Attitude-behavior link is strongly established in the literature for AVs. Erskine et al. (2020) investigating the consumer acceptance of fully autonomous vehicles revealed that attitude alone explains 75.7% of the variances in the behavioral intention. All the studies have unanimously established attitude as a significant predictor of behavioral intention. In many studies, attitude has been found to be the strongest predictor of behavioral intention to use AVs (Dai et al., 2021; Nastjuk et al., 2020; Zhang et al., 2019; Sener et al., 2019; Rahman et al., 2019). Marketing, advertising, creating pleasant experiences, and educating people on the potential values delivered by AVs enable users to develop a positive attitude towards AVs (Dai et al., 2021; Sener et al., 2019). Thus, we put forward the following hypothesis:

H5. Attitude has a positive effect on the behavioral intention to use AVs.

3.2.2 Hedonic motivation

Hedonic motivation refers to "fun or pleasure derived from using a technology" (Venkatesh et al., 2012). Ability of the AVs to free up the drivers' time enables them to consume various entertainment options while traveling actively. All the studies have unambiguously established hedonic motivation as a significant predictor of intention to use AVs (Kapser & Abdelrahman, 2020; Nordhoff et al., 2020a; Madigan et al., 2017). Studies have revealed that the novelty, fun, and entertainment options available in the AVs could significantly contribute to acceptance (Kapser and Abdelrahman, 2020; Madigan et al., 2017). Studies have also highlighted the need to design AVs with features such as social networking to enhance onboard comfort and enjoyment (Nordhoff et al., 2020a; Madigan et al., 2017). Thus, we put forward the following hypothesis:

H6. Hedonic motivation has a positive effect on the behavioral intention to use AVs.

3.2.3 Perceived benefit

Perceived benefit refers to the "consumer's subjective perceptions about the potential positive values derived from performing a target behavior"(Kim et al., 2009). Both direct and indirect benefits derived from AVs could influence the acceptance. Direct benefits include enhanced productivity of travelers while driving, reduction in stress of driving, and provision of mobility for the elderly. Indirect benefits include energy efficiency, emission control, safety, and efficient traffic movement (Manfreda et al., 2021). Perceived benefit is the balance construct in the risk-benefit analysis. Typically, technologies with higher perceived benefits and lower perceived risks will be accepted in the market. Thus, some studies have investigated both perceived benefit and risk together (Liu et al., 2019). The relationship between perceived benefit and behavioral intention to use AVs has been consistently supported in the literature (Manfreda et al., 2021; Liu et al., 2019b). Thus, we put forward the following hypothesis:

H7. Perceived benefit has a positive effect on the behavioral intention to use AVs.

3.2.4 Price evaluation

Price evaluation refers to the "consumer's cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them" (Venkatesh et al., 2012). Price value becomes positive when the benefits outweigh the cost (Tamilmani et al., 2021). Given that AVs are equipped with advanced sensors, navigation systems, LIDAR, and software, acquiring AVs involves considerable cash outlay. Thus, price evaluation could influence the acceptance of AVs. A few studies that investigated the relationship between price evaluation and behavioral intention to use AVs found it to be significant (Nastjuk et al., 2020; Seuwou et al., 2020; Herrenkind et al., 2019a). Studies have indicated that the cost of AVs is expected to reduce with mass production (Fagnant & Kockelman, 2018). Reduction in the price of AVs could enhance the cost-benefit ratio (Nastjuk et al., 2020) and pave the way for wider diffusion (Herrenkind et al., 2019a). Thus, we put forward the following hypothesis:

H8. Price evaluation has a positive effect on the behavioral intention to use AVs.

3.2.5 Perceived behavioral control

Perceived behavioral control refers to the “individual’s perception of ease or difficulty in performing a behavior of interest” (Ajzen, 1991); it is also influenced by the availability/non-availability of the required resources to perform target behavior (Yuen et al., 2020c). Relationship between perceived behavioral control and behavioral intention to use AVs was consistently supported in all the studies (Dai et al., 2021; Yuen et al., 2020c; Kaye et al., 2020; Buckley et al., 2018). Kaye et al. (2020) investigated the autonomous car's adoption and revealed that respondents were confident of operating AVs when they are commercially available. Yuen et al. (2020c) demonstrated that participants had access to necessary resources to operate AVs. Thus, we put forward the following hypothesis:

H9. Perceived behavioral control has a positive effect on the behavioral intention to use AVs.

3.3 Security context

3.3.1 Trust

Trust refers to “a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intention or behavior of another” (Rousseau et al., 1998). Consumer trust emanates from the cognitive assessment of the performance beliefs, perceived benefits, and potential risks associated with AVs. The “no trust, no use” principle that is validated for autonomous systems (Rousseau et al., 1998) would be applicable for AVs as well (Zhang et al., 2020). Trust in autonomous vehicles has been specified with three dimensions (Choi & Ji, 2015; Nastjuk et al., 2020): (1) *System transparency,* which refers to the user’s belief that the AVs provide a clearer view of the ability and its operation, (2) *Technical competence*, which refers to the users’ belief that the AVs meet the performance and reliability expectations, and (3) *Situation management*, which refers to the user’s belief that they could gain control over AVs whenever required. Numerous studies have investigated the relationship between trust and behavioral intention, and have found trust to be a significant predictor of behavioral intention to use AV’s (Du et al., 2021; Yuen et al., 2020e; Zhang et al., 2020; Nastjuk et al., 2020; Xu et al., 2018). A few studies have stated that trust is the strongest determinant for adopting AVs (Du et al., 2021; Hegner et al., 2019; Liu et al., 2019; Choi & Ji, 2015). Studies have posited that AV manufacturers can build public trust by guiding media to report more positive experiences and benefits, involving the public in AV developmental initiatives, and fostering transparency to address ethical issues and moral dilemmas. Thus, we put forward the following hypothesis:

H10. Trust has a positive effect on the behavioral intention to use AVs.

3.3.2 Perceived safety

Perceived safety in the AV context refers to "a climate in which drivers and passengers feel relaxed, safe and comfortable while driving" (Xu et al., 2018). Safety incidents in the automotive sector could be related to the vehicle, infrastructure, environmental, and human-related factors (Montoro et al., 2019). Human error alone contributes to 75% of safety-related incidents (Stanton & Salmon, 2009). Emulating drivers with the promise of assuring safety by reducing the accidents caused by traffic violations and human misjudgments have been the primarily driver of AV development. However, at present, not everyone is convinced that the performance of AVs would match that of human drivers (Manfreda et al., 2021). Serious safety-related incidents reported in recent times might also hamper the intention to use AVs (Sener et al., 2019). Thus, perceived safety could play a decisive role in the adoption of AVs. As expected, all the studies have reported significant results for the relationship between perceived safety and behavioral intention to use AVs (Manfreda et al., 2021; Seuwou et al., 2020; Sener et al., 2019). Enhancing the safety aspects and making the consumers experience the safety features available in the AVs are crucial for promoting AV adoption (Xu et al., 2018). Thus, we put forward the following hypothesis:

H11. Perceived safety has a positive effect on the behavioral intention to use AVs.

3.3.3 Privacy risk

Perceived risk refers to "an expected negative utility that consumers associated with purchasing a particular product or service" (Snyder, 1986). According to prospect theory, individuals tend to weigh product risks and uncertainty more than gains. Potential risks in AV include functional failure leading to possible accidents (Jing et al., 2021). Privacy risks associated with AVs include data misuse and software hacking (Zhu et al., 2020). Thus, perceived risk is considered as an antecedent of AV adoption. However, findings from earlier studies revealed mixed responses for the impact of perceived risk on the behavioral intention to use AVs. While a few studies found this relationship significant (Jing et al., 2021; Zhu et al., 2020; Kapser & Abdelrahman, 2020), others reported non-significant results (Liu et al., 2019b; Choi & Ji, 2015). The studies which established the significance of perceived risk suggested that issuing statements explaining the safety features (Jing et al., 2021), utilizing social media to spread the positive features by word of mouth (Zhu et al., 2020) and introducing a human-like avatar to present basic information and collect user feedback (Lee et al., 2019a), would greatly enhance perceived privacy. Thus, we put forward the following hypothesis:

H12. Perceived risk has a negative effect on the behavioral intention to use AVs.

3.4 Level of automation as moderator

The level of automation is the contextual exigency investigated in the adoption of AVs. The Society of Automation Engineers (SAE) proposed six levels of automation, which varied from Level 0 (no automation) to Level 5 (full automation) (SAE, 2016). Yet, only levels 3-5 support autonomous driving (Kaye et al., 2020). Level 3 represents conditional automation; Level 4 represents high automation, and Level 5 represents full automation. Several studies have investigated the adoption intention of Level 3 (conditional automation) (Zhang et al., 2020; Zhang et al., 2019; Xu et al., 2018); Level 4 (high automation) (Dai et al., 2021; Kaye et al., 2020; Madigan et al., 2017) and Level 5 (Du et al., 2021; Baccarella et al., 2020; Rahman et al., 2019; Choi & Ji, 2015) (full automation) automation in AVs. Most of the prior studies on AVs have investigated only one level of automation. However, differences in the relationship between the determinants of the behavioral intention to use AVs concerning the level of automation is not clear. It would be of great relevance for the AV manufacturers to understand the impact of automation levels on the adoption intention.

Extant research revealed the differences in the antecedents of AV adoption based on the level of automation. For instance, most studies focusing on Level 3 AVs found perceived ease of use as a significant determinant (Man et al., 2020; Zhang et al., 2019). In contrast, some studies that focused on Level 4 and above revealed non-significant results (Nastjuk et al., 2020; Choi & Ji, 2015). This shows the decreasing relevance for the perceived ease of use with the increasing levels of automation. Divergent findings were reported for the relationship between the perceived ease of use and behavioral intention. For the relationship between perceived usefulness and attitude, some Level 3 studies found a non-significant relationship (Man et al., 2020; Zhang et al., 2019), whereas, all the studies based on Level 4 and above exhibited a significant relationship (Jing et al., 2021). We may expect the impact sizes of the relationship between the antecedents of AV adoption to vary based on the levels of automation. Thus, we put forward the following hypothesis:

H13. The level of automation moderates the relationship between the antecedents of behavioral intention to use AVs.

3.5 Vehicle ownership as moderator

Extant research on AV adoption has predominantly focused on public transport (Dai et al., 2021; Zhu et al., 2020; Madigan et al., 2017) and private transport (Du et al., 2021; Baig & Mir, 2020; Liu et al., 2019a; Xu et al., 2018). There exists a significant difference between the way public users and private users perceive AVs. Firstly, to own a private AV, one must incur considerable cash outlay, which is not so in the case for public vehicles. Secondly, private owners should be persuaded to adopt AVs with personal (energy, time, and cost savings) and social benefits. Whereas personal benefits would not play a key role to the public AV users as the costs and benefits are to be borne either by the governments or by the public service providers. Creating awareness about the social benefits should drive the adoption of public AVs. Moreover, studies examining the differences in AVs' public and private adoption are lacking in the literature. Hence, the present study investigated the moderating role of vehicle ownership (public, private) in the adoption AVs.

Qualitative analysis from the prior studies revealed divergent perspectives on the adoption of AVs based on vehicle ownership. For example, all the studies that investigated the private adoption of AVs consistently found the relationship between the perceived usefulness and behavioral intention as significant (Hryniewicz & Grzegorczyk, 2020; Hegner et al., 2019). Surprisingly, some studies on the public adoption of AVs found a non-significant impact of perceived usefulness on behavioral intention (Herrenkind et al., 2019a). This indicates that not all public transport users are convinced that AVs add value to their travel experience. Further, in public AV context, most of the studies observed a significant relationship between effort expectancy and behavioral intention (Bernhard et al., 2020; Madigan et al., 2016); whereas the same relationship was found to be non-significant in the private AV context (Nordhoff et al., 2020a; Kettles & Van Belle, 2019). Contrasting results were obtained for the relationship between the facilitating condition and behavioral intention - all public AV-based studies reported significant results (Nordhoff et al., 2020b; Madigan et al., 2017), and all private AV-based studies reported non-significant results (Kaye et al., 2020; Nordhoff et al., 2020a). Given the heterogeneity between the public and private adoption of AVs, we put forward the following hypothesis:

H14. Vehicle ownership moderates the relationship between the antecedents of the behavioral intention to use AVs.

3.6 Culture as moderator

Differences in transportation and automation culture across the eastern and western cultures could influence the adoption of AV technology (Wang et al., 2020). Most studies on AV adoption have investigated the behavioral intention in a single country context (Jing et al., 2021; Dai et al., 2021; Du et al., 2021). A few studies did investigate AV adoption by taking samples from multiple countries (Kaye et al., 2020; Nordhoff et al., 2020a; Madigan et al., 2016), but they were all from western cultures. Müller (2019) attempted a cross-cultural analysis by drawing samples from Europe, US, and China. However, the study has not exclusively focused on AV technology. Studies investigating the cross-cultural differences in AV adoption are currently lacking in the literature.

Eastern cultures exemplify collectivism, whereas western cultures value individualism (Hofstede, 2011). Aspects relating to family and social groups drive the behavior in a culture of collectivism. On the other hand, personal desires and attitudes govern the behavior of people in a culture of individualism (Wong & Cheng, 2020). Thus, we expect the impact of social influence on behavioral intention to use AVs be highly significant in eastern cultures. Extant studies have revealed divergent perspectives on the relationship between social influence and behavioral intention to use AVs. For instance, most of the studies conducted in eastern cultures revealed social influence as a significant predictor of behavioral intention (Liu et al., 2020; Zhang et al., 2020; Baig & Mir, 2020). However, studies performed in a western milieu found the impact of social influence on behavioral intention to use AVs to be insignificant (Nastjuk et al., 2020; Kaye et al., 2020; Nordhoff et al., 2020b). Further, we expect the impact of attitude on behavioral intention to be significant in individualistic western cultures.

Eastern cultures epitomize femininity, whereas western cultures characterize masculinity (Mehta et al., 2021). While feminine cultures greatly emphasize quality of life, interpersonal relationships, and a friendly atmosphere, masculine cultures emphasize task orientation, challenge, and goal accomplishment. In the context of AVs, we expect the relationship between ease of use and behavioral intention to be highly significant in eastern cultures. Prior studies have reflected this divergence. For all the studies conducted in eastern cultures, perceived ease of use had a positive impact on behavioral intention (Jing et al., 2021; Wu et al., 2019; Zhu et al., 2020). However, some of the studies conducted in western cultures revealed a negative impact of perceived ease of use on behavioral intention (Kaye et al., 2020; Bruckes et al., 2019; Nordhoff et al., 2020b; Madigan et al., 2017). Moreover, hedonic motivation to drive AVs is expected to have significant impact in the western cultures. Overall, we expect culture to have an impact on the antecedents of AV adoption. Thus, we propose the following hypothesis:

H15. Culture moderates the relationship between the antecedents of behavioral intention to use AV's.

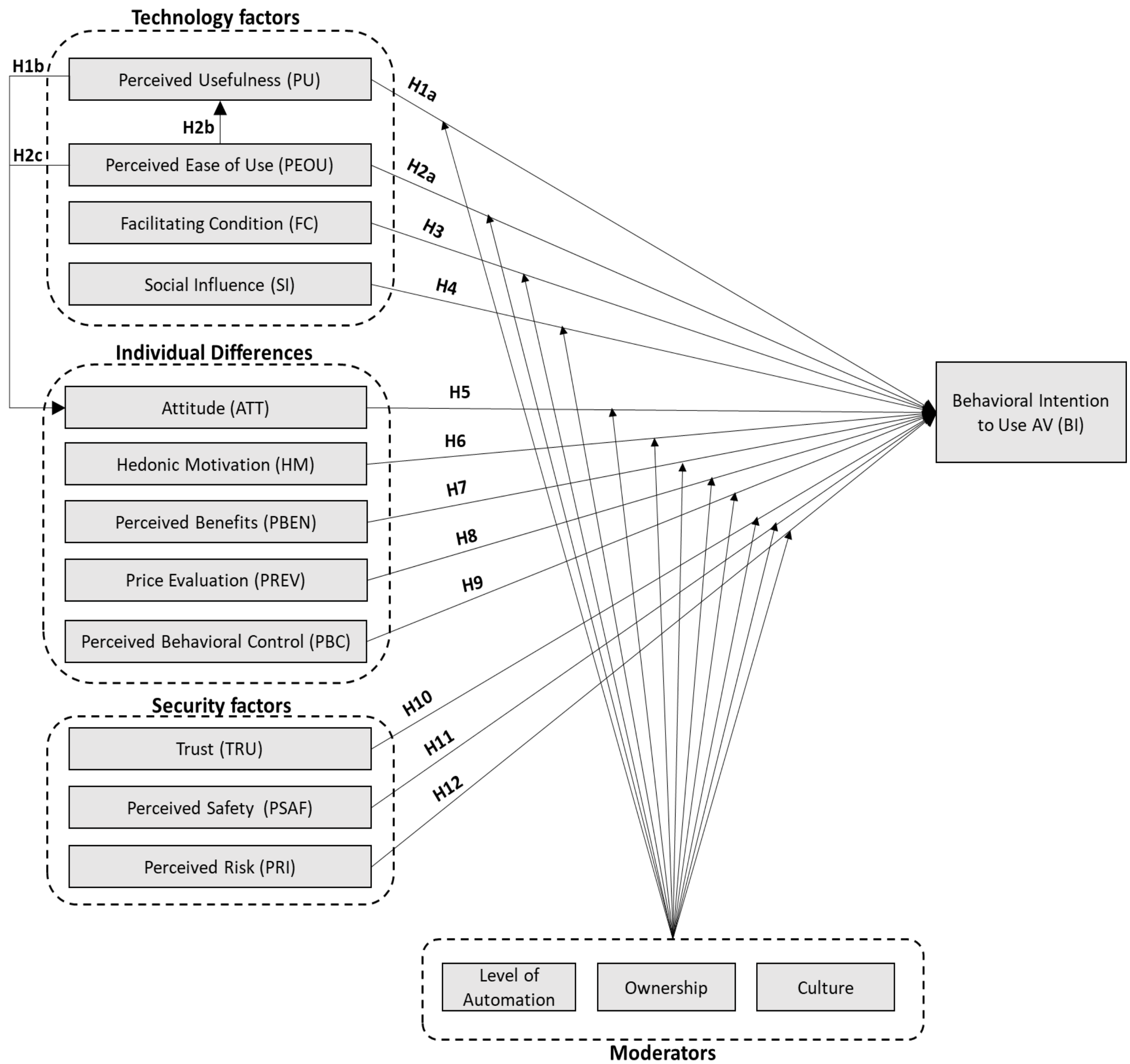

Fig.1 Research model and hypothesis

4. Data & *Methods*

4.1 Study retrieval and selection

To identify the potential empirical studies for inclusion, we followed four search strategies. First, we performed a comprehensive literature search in multiple databases such as, Web of Science, Scopus, IEEE Xplore, Google scholar, and Science direct. Initially, we identified all the potential keywords, i.e., “autonomous”, “automated”, “self-driving”, “driverless”, “vehicle”, “transport”, “driving”, “acceptance”, and “adoption”. The logical combinations of keywords were applied to multiple databases to locate potential studies (Table 1). Second, we manually searched the leading journals in this domain, including Accident analysis and prevention, Transportation research part A, Transportation research part C, Transportation research part D, Transportation research part F, and Safety science. Third, we consulted previous systematic reviews (Jing et al. 2020; Alawadhi et al. 2020; Golbabaei et al. 2020; Bornholt & Heidt (2020) to extract relevant articles. Fourthly, we adopted the backtracking or descendancy approach, wherein we revisited the reference section of the selected articles to identify the missing papers. Finally, articles shortlisted for the study comprised of published conference proceedings and journal articles (Jadil et al., 2021; Jeyaraj, 2022a).

Table 1: Search keywords

S. No.	Keywords combination
1	("autonomous" AND "driving" AND ("acceptance" OR "adoption"))
2	("automated" AND "driving" AND ("acceptance" OR "adoption"))
3	("automated" AND "vehicle*" AND ("acceptance" OR "adoption"))
4	("autonomous" AND "vehicle*" AND ("acceptance" OR "adoption"))
5	("autonomous" AND "transport" AND ("acceptance" OR "adoption"))
6	("automated" AND "transport" AND ("acceptance" OR "adoption"))
7	("driverless") AND ("adoption" OR "acceptance")
8	("self-driving") AND ("adoption" OR "acceptance")
9	(“robo” AND “taxi” and “AND (“acceptance” OR “adoption”))

As per the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA), the study selection process is depicted in Fig.2. Search from all the possible databases yielded 2,199 records. After the removal of duplicates, 1,917 unique records were created. Title and abstracts of 1,917 records were screened based on the main criterion that the article must empirically investigate the adoption of AVs. The full text of each of the 122 publications was carefully screened by applying the four inclusion criteria. First, we included studies that empirically investigated the adoption of AVs. Second, we considered only studies that investigated at least one bivariate relationship between antecedents and consequences of AV adoption. Third, we analyzed only articles written in the English language. Fourth, we included studies that had reported the quantitative information (i.e., sample size, correlation, effect size, or regression coefficient, etc.) essential to performing effect size analysis. This resulted in 60 articles. Finally, we considered only bivariate relationships that have been investigated in at least five studies. Two primary studies that did not investigate any of the selected bivariate relationships were excluded. Even though meta-analysis can be performed with the minimum of three samples (Oh et al., 2011), it was found that meta-analysis performed using smaller samples (<5) suffer sampling error (Schmidt & Oh, 2013). Thus, we considered only relationships investigated in at least five studies. Also, when one article reported the results of two or more independent studies, these were treated as separate studies for analysis (Zhao et al., 2018). For instance, Kaye et al. (2020) independently reported findings on the adoption of highly autonomous cars from the three countries (Australia, France, and Sweden); this has been treated as three different studies. Complete list of studies and corresponding articles have been listed in Appendix 1.

Based on these four criteria, 65 studies identified from 58 articles were included in the meta-analysis. The final sample includes 50 journal articles (86.21%) and 8 conference proceedings/book chapters (13.79%). Characteristics of the studies have been included in the meta-analysis are shown in Appendix 1.

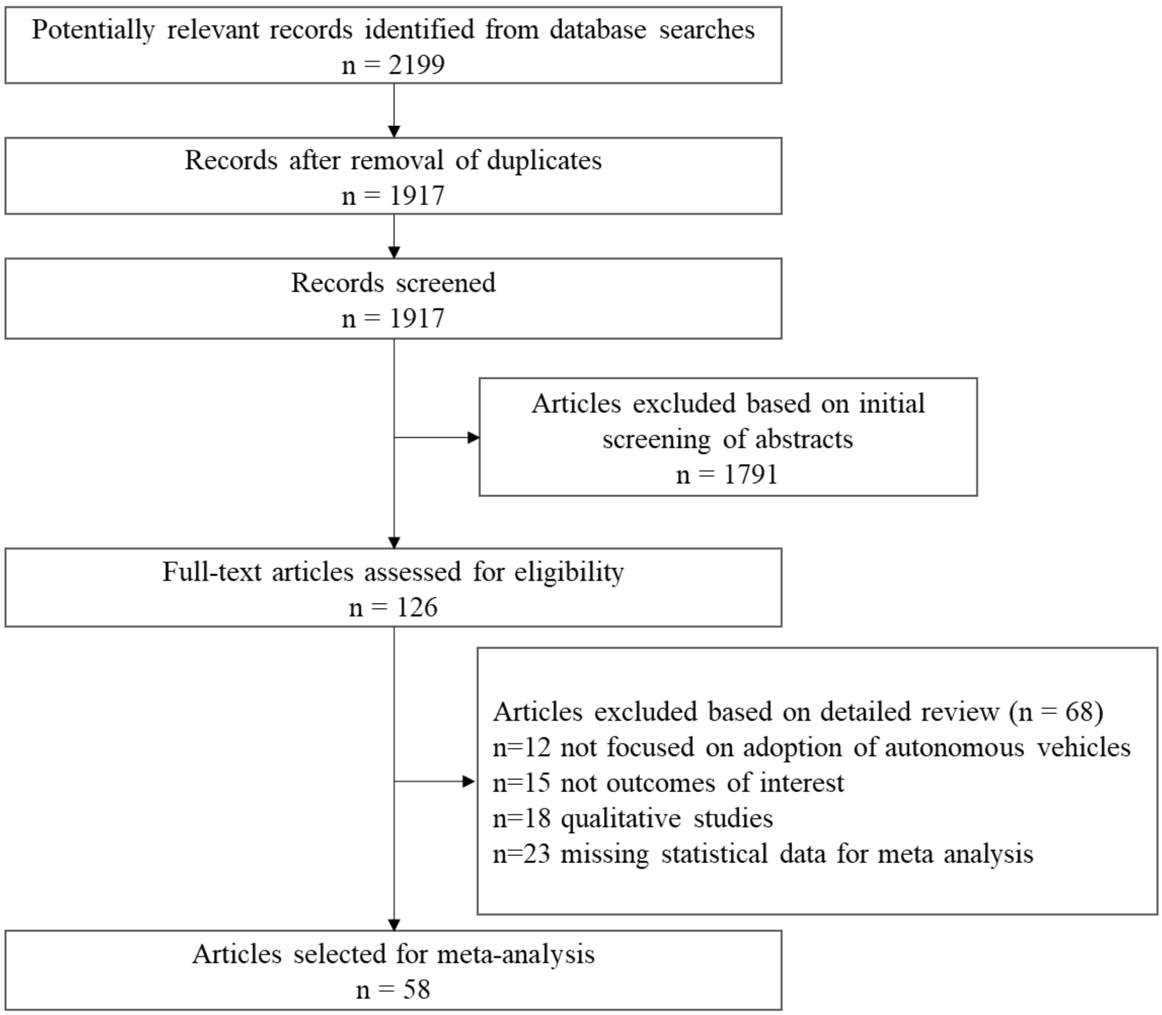

Fig.2 Study selection process

4.2 Coding procedure

The first step was to develop a coding scheme. For each of the selected articles, information on nine attributes were extracted - author and year of publication, source, theoretical base, country of origin of the sample, sample size, effect size, reliability estimate (Cronbach alpha or composite reliability), level of automation considered in the study (if reported), and vehicle ownership (public or private). The first coder independently coded all the articles and correlations (N=245), and the second coder randomly reviewed 100 items to assess the reliability. As a robust coding procedure was adopted, very little scope existed for subjectivity or conflicts. The agreement between the coders was estimated to be 97% (N=97) and the cases of discrepancies were resolved through discussion and mutual consensus.

4.3 Statistical analysis

Statistical analysis was performed in three phases – weight analysis, effect size analysis, and moderator analysis.

4.3.1 Weight analysis

In the first phase, we performed weight analysis for all the relationships presented in the research model. The study used the weight analysis to understand the number of times a particular relationship was investigated, and to depict their dominance in understanding the adoption of AV (Jeyaraj et al., 2006). Similarly, the relationship's rate of significance indicates not only the predictive power but also the convergence or divergence of the relationships in AV adoption. The study adopted the weight analysis to draw a pooled conclusion for the non-significant (conflicting) relationships. When the rate of significance is less than 80%, that relationship is considered as inconsistent (Rana et al., 2015).

4.3.2 Effect size analysis

The random-effects-model was preferred over fixed effects-model when the studies significantly differed in terms of technology, nationality, and participants (Jeyaraj & Dwivedi, 2020). Owing to the heterogeneity in AV adoption studies in terms of level of automation and sample origin, the present study adopted a random-effects model to synthesize the correlations drawn from multiple studies.

Fisher’s transformation of the correlation was calculated using the following formula:

$$T_i = 0.5 * \ln\left(\frac{1+r_i}{1-r_i}\right)$$

Pooled correlations are affected by sampling error because the primary studies cannot cover the entire population. Correlation coefficients are also affected by measurement error (Hunter & Schmidt, 2004). To correct these errors, we used the Fisher’s transformation adjusted by sample size to calculate the combined effect size:

$$T\ (\text{adjusted}) = \sum W_i * T_i$$

Where, W_i is the sample size of the specific study, and T_i is the Fisher’s transformation.

The cumulative effect size was calculated as:

$$r_c = \frac{e^{2T\,(adjusted)} - 1}{e^{2T\,(adjusted)} + 1}$$

Along with the point estimate of cumulative effect size, we also calculated the 95% confidence interval for each of the pairwise relationships included in the study.

Heterogeneity across the studies was tested using Q-statistic and I^2 estimate. Q-statistic investigated the null hypothesis that all studies have similar effect size. Rejection of the null hypothesis ($p<0.05$) confirmed the presence of heterogeneity and justified the selection of a random-effects model. I^2 value explained the percentage of inconsistency across the studies for the relationship being investigated. I^2 value exceeding 60% reaffirmed the existence of heterogeneity. The Q-statistic and I^2 values were calculated as follows:

$$Q = \sum W_i * T_i^2 - \frac{\sum W_i * T_i{}^2}{\sum W_i}$$

$$I^2 = \frac{Q - df}{Q}$$

Degrees of freedom, df = number of studies - 1

4.3.3 Publication bias

Publication bias is a serious threat to meta-analytic studies which question the robustness of the findings. We used a combination of trim and fill, Precision Effect Test, and Precision Effect Estimate with Standard Error (PET-PEESE) (Kepes & Thomas, 2018) to assess publication bias. We do not consider Rosenthal (1991) fail-safe N, a commonly used method to assess the publication bias, owing to multiple criticisms and difficulty in interpreting the N value (Fragkos et al., 2014). Fail-safe N neither estimates the publication bias-adjusted effect size nor provides the confidence interval.

The trim and fill approach is used as it calculates the effect size and the confidence interval by accounting for the missing effects of unpublished studies (Duval and Tweedie, 2000a; Duval and Tweedie, 2000b). First, a funnel is created by plotting the observed effect sizes against the standard error. Then, the funnel plot is scrutinized to bring out the asymmetry present on either side of the funnel. In case of asymmetry, missing studies are imputed in the funnel to create funnel plot symmetry. Finally, the effect size and confidence interval will be calculated after imputing the missing studies.

Further, we applied meta-regression models PET and PEESE (Stanley & Doucouliagos, 2014) to assess the publication bias and calculate the effect size after making adjustments for the bias. The PET uses standard error to assess publication bias, while PEESE uses variance to correct publication bias. However, PET-PEESE results are to be interpreted together (Stanley & Doucouliagos, 2014). PET is a qualifier; it tells whether it is possible to measure the true effect size by making adjustments for publication bias (Stanley & Doucouliagos, 2014). Thus, if PET is significant, it indicates that correction for the publication bias can be made. In such a scenario, PEESE provides a genuine effect size by significantly minimizing the publication bias. Otherwise, if PET is insignificant, apparently, it indicates that there is no publication bias, and the correction to the effect size cannot be made.

4.3.4 Moderator analysis

In the final phase of the analysis, we conducted the moderator analysis to explore the potential factors causing the heterogeneity. This study investigated the presence of contextual moderators (i.e., level of automation and vehicle ownership) and culture, which are expected to potentially impact the adoption of AVs.

For the first moderator, the studies were classified based on the level of automation, which is Levels 3, 4, and 5. Level 3 (conditional automation) supports limited automated driving capability (Du et al., 2021). Different driving modes in Level 3 automation includes automated driving, period of control transfers and manual driving (Buckley et al., 2018). AVs with Levels 4 and 5 support fully automated driving with "hands off, eyes off, and minds off" (Yuen et al., 2020e). Hands off – free from operating steering and acceleration; eyes off – free from monitoring external environment; minds off – ad-hoc based intervention if required. Even though Level 4 AVs are equipped with steering and pedals, they are capable of performing the driving activity even if the driver doesn't respond to driving request (Kaye et al., 2020). For these reasons, we considered Level 3 as one group, and Levels 4 and 5 together as another group. Similarly, for the second moderator, we classified the studies based on vehicle ownership into public and private. For the purpose of conducting meta-analysis on espoused culture, articles were classified as eastern and western based on the sample nationality (Mehta et al., 2021; Sarkar et al., 2020). Only bivariate relationships that have been investigated in at least two studies by both the groups were considered for analysis (Hunter & Schmidt, 2004). Then a subgroup analysis was conducted to examine the mean differences in effect size between the two groups. Between-group Q-value was used to assess the sub-group differences. The meta-analysis for the study was carried out using the software Comprehensive Meta-Analysis (CMA) version 3.

Table 2: Descriptive statistics

Relationship	Number of studies	Range		Weight analysis				Sample Range		Cumulative Sample Size	Average Sample Size
		Lower	Upper	Significant	Non-Significant	Significant (%)	Inconsistency	Lower	Upper		
Technology factors											
PU - BI (H1a)	42	-0.07	0.74	38	4	90.48	No	74	9118	27665	659
PU - ATT (H1b)	10	0.075	0.485	9	1	90	No	116	1765	5287	529
PEOU - BI (H2a)	35	-0.29	0.7	19	16	54.29	Yes	74	9118	25777	736
PEOU - PU (H2b)	23	0.02	0.88	19	4	82.61	No	116	1177	8503	370
PEOU - ATT(H2c)	10	-0.035	0.427	8	2	80	No	116	1765	5287	529
FC - BI (H3)	8	-0.095	0.33	4	4	50	Yes	315	9118	12253	1532
SI - BI (H4)	27	0.047	0.419	23	4	85.18	No	74	9118	20610	763
Individual differences											
ATT - BI (H5)	21	0.136	0.892	21	0	100	No	74	3097	12013	572
HM - BI (H6)	11	0.18	0.5	11	0	100	No	62	9118	11936	1085
PBEN - BI (H7)	6	0.15	0.4	6	0	100	No	300	441	2165	361
PREV - BI (H8)	6	-0.281	0.193	5	1	83.33	No	116	501	1761	294
PBC - BI (H9)	6	0.108	0.71	6	0	100	No	74	625	2022	337
Security factors											
TRU - BI (H10)	25	0.038	0.59	23	2	92	No	74	700	8912	356
PSAF - BI (H11)	7	0.106	0.596	7	0	100	No	300	3097	6153	879
PRI - BI (H12)	8	-0.173	-0.03	5	3	62.5	Yes	313	552	3244	406

Note: PU = Perceived usefulness, PEOU = Perceived ease of use, FC = Facilitating condition, TRU = Trust, PSAF = Perceived safety, PRI = Perceived risk, ATT = Attitude, HM = Hedonic motivation, PBEN = Perceived benefits, PREV = Price evaluation, PBC = Perceived behavioral control

*p<0.05, **p<0.02, ***p<0.001

5. Results

5.1 Descriptive statistics

According to the research model, summary statistics of the relationship between the antecedents of behavioral intention to adopt AVs are presented in Table 2. The relationships were classified as technological factors (perceived usefulness, perceived ease of use, facilitating condition and social influence), individual differences (attitude, hedonic motivation, perceived benefits, price evaluation, and perceived behavioral control) and security factors (trust, perceived safety, and perceived risk). The average sample size for all the 15 relationships exceeded 300.

Relationship between perceived usefulness and behavioral intention is the most widely investigated relationship. Of the 38 investigations, perceived usefulness was a significant predictor of behavioral intention in 34 studies (90.48%). Further, the relationship between social influence and behavioral intention (27 studies), and trust and behavioral intention (25 studies) have been the dominant relationships with the significance of 85.18% and 92%, respectively. The impact of attitude, hedonic motivation, perceived benefits, perceived behavioral control, and perceived safety, on the intention to use AVs has been significant in all the studies that investigated these relationships.

Our weight analysis revealed inconsistent findings for three relationships (i.e., perceived ease of use → behavioral intention, facilitating condition → behavioral intention, and perceived risk → behavioral intention). The inconsistencies identified from the cumulative analysis have been duly considered in the meta-analysis.

5.2 Meta-analysis results

This study aimed to estimate the combined effect sizes and their significance for the relationships proposed in the conceptual model. Accordingly, 15 path coefficients corresponding to relationships H1a-H12 were included in the analysis. Table 3. summarizes the results of meta-analysis (combined effect size and confidence interval), and heterogeneity statistics (Q and I^2). Findings from the study revealed support for 13 of the 15 relationships investigated. All the technical factors were found to be significantly related to the behavioral intention to use AVs, except for facilitating condition (H3). Thus, hypotheses H1a-H2c and H4 were supported. Notably, technical attribute perceived usefulness (H1b: β =0.363; $p<0.001$) emerged as the strongest predictor of behavioral intention. The relationships between the individual differences and behavioral intention to use AVs were found to be significant for all the constructs except price evaluation (H8). Thus, the hypotheses H5-H7 and H9 were supported. All the security factors (H10-H12) investigated in this study were significant. Among the security factors, trust (H10: β =0.315; $p<0.001$) emerged as the strongest determinant of intention to use AVs. The cumulative impact of dominant behavioral theories (i.e., TPB, TAM, UTAUT) and contextual factors in the adoption of AVs derived from the meta-analysis are presented in Fig.4.

Table 3: Meta-analytic results of pairwise relationships

Relationship	r-mean	Combined effect size	95% CI	Heterogeneity	
				Q-value	I-squared
Technology Factors					
PU - BI (H1a)	0.348	0.363***	0.29-0.43	1598.810***	97.43
PU - ATT (H1b)	0.295	0.304***	0.22-0.38	82.184***	89.05
PEOU - BI (H2a)	0.134	0.137***	0.09-0.18	387.030***	91.22
PEOU - PU (H2b)	0.356	0.389***	0.28-0.49	770.245***	97.14
PEOU - ATT (H2c)	0.22	0.224***	0.11-0.33	140.445***	93.59
FC - BI (H3)	0.086	0.083ns	-0.02-0.18	113.650***	93.84
SI - BI (H4)	0.193	0.198***	0.14-0.25	317.955***	91.82
Individual Differences					
ATT - BI (H5)	0.481	0.520***	0.40-0.62	1326.318***	98.49
HM - BI (H6)	0.309	0.316***	0.21-0.41	156.044***	93.59
PBEN - BI (H7)	0.258	0.263***	0.18-0.34	22.583***	77.86
PREV - BI (H8)	0.025	0.024ns	-0.14-0.19	64.279***	92.22
PBC - BI (H9)	0.301	0.321**	0.09-0.51	132.175***	96.22
Security Factors					
TRU -BI (H10)	0.304	0.315***	0.25-0.37	340.048***	92.94
PSAF - BI (H11)	0.271	0.283***	0.15-0.40	138.979***	95.68
PRI - BI (H12)	-0.1	-0.100***	-0.14-0.06	8.498ns	17.63

Notes: PU = Perceived usefulness, PEOU = Perceived ease of use, FC = Facilitating condition, TRU = Trust, PSAF = Perceived safety, PRI = Perceived risk, ATT = Attitude, HM = Hedonic motivation, PBEN = Perceived benefits, PREV = Price evaluation, PBC = Perceived behavioral control

*p<0.05, **p<0.02, ***p<0.001

Combined effect size analysis helps to ascertain the strength of bivariate relationships between the constructs. According to this categorization, effect size close to 0.1 indicates weak impact, 0.3 indicates moderate impact, and 0.5 reflects strong impact (Cohen et al., 2014). Relationships with trivial effect sizes (i.e., facilitating condition → behavioral intention, price evaluation → behavioral intention)) were non-significant. Most of the significant relationships exhibited moderate impact. Two paths, perceived ease of use → behavioral intention, and perceived risk → behavioral intention had low impacts. The relationship attitude → behavioral intention had a strong impact; the remaining relationships exhibited moderate effect size.

Heterogeneity analysis performed using the Q-test established the statistical significance of 14 of the 15 relationships. The relationship, privacy risk → behavioral intention was found to be non-significant. I^2 values for all the significant paths exceeded 70%. High heterogeneity reported across the hypothesized relationships favored the selection of random-effects model for combined effect size analysis.

5.3 Publication bias

This study assessed the publication bias for the hypothesized relationships using the combination of trim and fill and PET-PEESE methods. Results of the publication bias tests are shown in Table 4. The table simultaneously presents the effect size of the baseline meta-analysis and the bias-corrected effect sizes calculated using trim and fill and PET-PEESE approaches.

First, trim and fill is an intuitive approach that visually depicts the funnel asymmetry, imputes the missing studies, and calculates the corrected effect size and confidence interval. For illustration, we explain the trim and fill result for the relationships, perceived usefulness → behavioral intention. The funnel plot of effect sizes drawn against the standard error for PU → BI is shown in Fig. 3 (A). As shown in Table 4, eight missing studies have been identified for the relationship PU → BI. Further, the funnel plot with the imputed missing studies is shown in Fig. 3(B). Consequently, the trim and fill corrected effect size was estimated to be 0.452. It can be inferred that the baseline effect size (0.363) is underestimated. The difference between the trim and fill adjusted effect size and the baseline effect size, delta ($\Delta ES_{t\&f}$=0.089), revealed the presence of "low" publication bias for PU → BI (Kepes & Thomas, 2018).

Second, the PET-PEESE algorithm is leveraged to test the publication bias. For illustration, we took the relationship PU → BI. The significance of perceived usefulness in PET analysis confirmed the scope for effect size adjustment. Thus, the true effect size was inferred from PEESE estimation. PEESE corrected effect size for PU → BI was estimated to be 0.386. This result also indicated that the baseline effect size was slightly underestimated. Further, the difference between the PEESE adjusted effect size and the baseline effect size, delta (ΔES_{PEESE} =0.023), revealed the presence of "negligible" publication bias for PU → BI (Kepes & Thomas, 2018).

Table 4: Results of the publication bias

Relationship	Baseline		Trim and fill					PET			PEESE		
	ES_B	95% CI	is	$ES_{t\&f}$	p-value	95% CI	$\Delta ES_{t\&f}$	ES_{PET}	p-value	ΔES_{PET}	ES_{PEESE}	p-value	ΔES_{PEESE}
Technology factors													
PU - BI (H1a)	0.363^{***}	0.29-0.43	8	0.452	0.00	0.38-0.52	0.089	0.399	0.00	0.036	0.386	0.00	0.023
PU - ATT (H1b)	0.304^{***}	0.22-0.38	2	0.354	0.00	0.26-0.45	0.050	0.426	0.00	0.122	0.375	0.00	0.071
PEOU - BI (H2a)	0.137^{***}	0.09-0.18	0	0.137	0.00	0.08-0.20	0.000	0.055	0.55	-0.082	0.098	0.05	-0.039
PEOU - PU (H2b)	0.389^{***}	0.28-0.49	0	0.389	0.00	0.28-0.54	0.000	0.330	0.21	-0.059	0.361	0.01	-0.028
PEOU - ATT (H2c)	0.224^{***}	0.11-0.33	0	0.224	0.00	0.12-0.33	0.000	0.213	0.18	-0.011	0.219	0.03	-0.005
FC - BI (H3)	0.083^{ns}	-0.02-0.18	0	0.083	0.09	-0.08-0.17	0.000	-0.19	0.03	-0.273	-0.12	0.02	-0.207
SI - BI (H4)	0.198^{***}	0.14-0.25	6	0.235	0.00	0.19-0.28	0.037	0.313	0.00	0.115	0.336	0.00	0.138
Individual differences													
ATT - BI (H5)	0.520^{***}	0.40-0.62	3	0.642	0.00	0.49-0.78	0.122	0.839	0.00	0.319	0.687	0.00	0.167
HM - BI (H6)	0.316^{***}	0.21-0.41	2	0.361	0.00	0.28-0.43	0.045	0.426	0.00	0.110	0.362	0.00	0.046
PBEN - BI (H7)	0.263^{***}	0.18-0.34	0	0.263	0.00	0.18-0.36	0.000	0.433	0.00	0.170	0.424	0.00	0.161
PREV - BI (H8)	0.024^{ns}	-0.14-0.19	1	-0.013	0.45	-0.15-0.12	-0.037	-0.06	0.84	-0.089	-0.001	0.89	-0.025
PBC - BI (H9)	0.321^{**}	0.09-0.51	0	0.321	0.01	0.09-0.57	0.000	0.135	0.69	-0.186	0.254	0.21	-0.067
Security factors													
TRU -BI (H10)	0.315^{***}	0.25-0.37	0	0.315	0.00	0.23-0.38	0.000	0.413	0.00	0.098	0.351	0.00	0.036
PSAF - BI (H11)	0.283^{***}	0.15-0.40	2	0.356	0.00	0.21-0.49	0.073	0.392	0.16	0.109	0.351	0.06	0.068
PRI - BI (H12)	-0.100^{***}	-0.14-0.06	0	-0.100	0.00	-0.14--0.06	0.000	0.003	0.48	0.103	-0.048	0.38	0.052

Notes: ES_B = baseline effect size, CI = confidence interval, is = trim and fill imputed samples, ESt&f = trim and fill adjusted effect size, ΔESt&f = difference between trim and fill adjusted effect size and baseline effect size, ESPET = PET adjusted effect size, ΔESPET = difference between PET adjusted effect size and baseline effect size, ESPEESE = PEESE corrected effect size, ΔESPEESE = difference between PEESE corrected effect size and baseline effect size

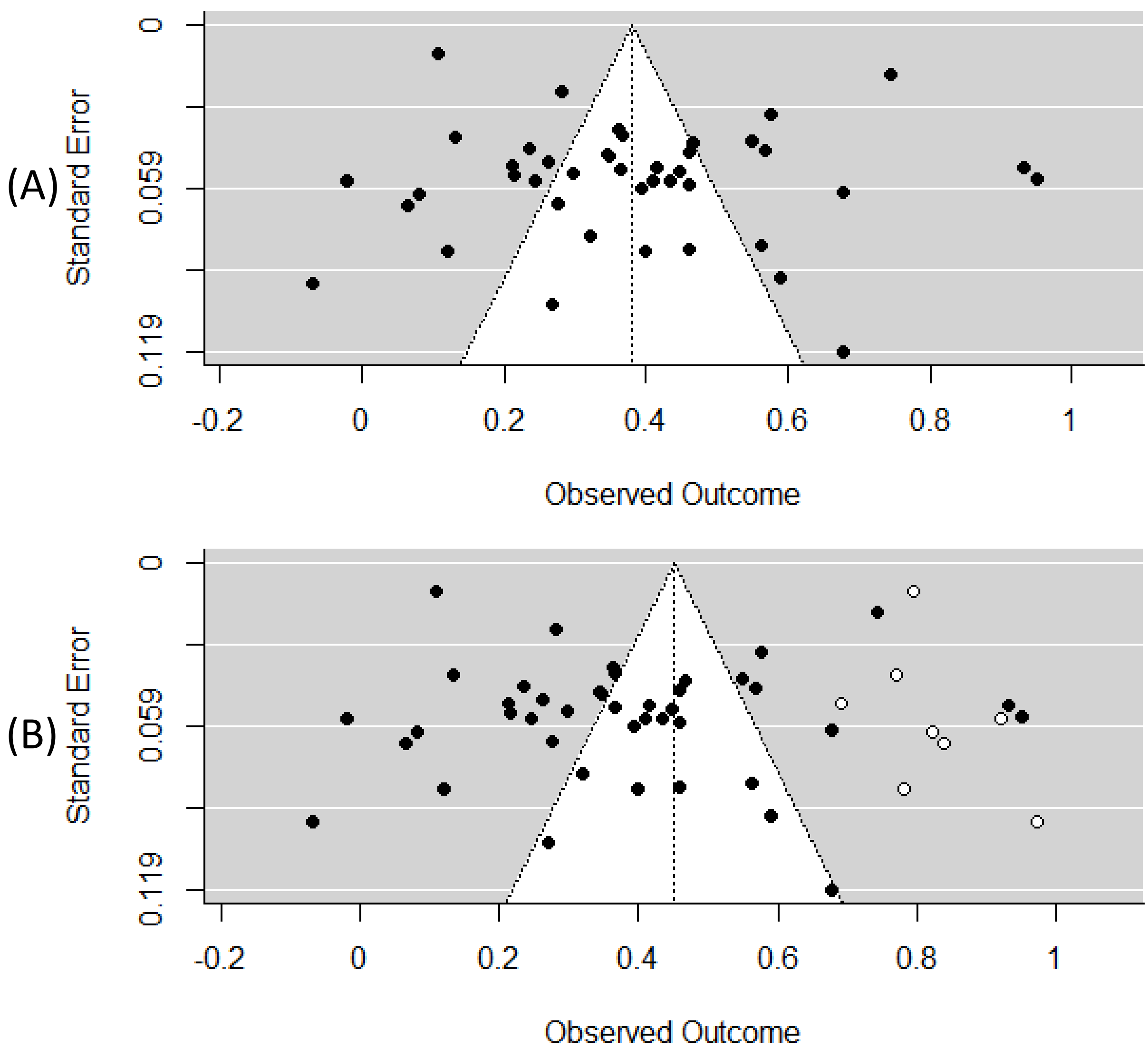

Fig.3 (A) Funnel plot for the relationship PU → BI, (B) Missing studies imputed (white dots) trim and fill funnel plot for the relationship PU → BI

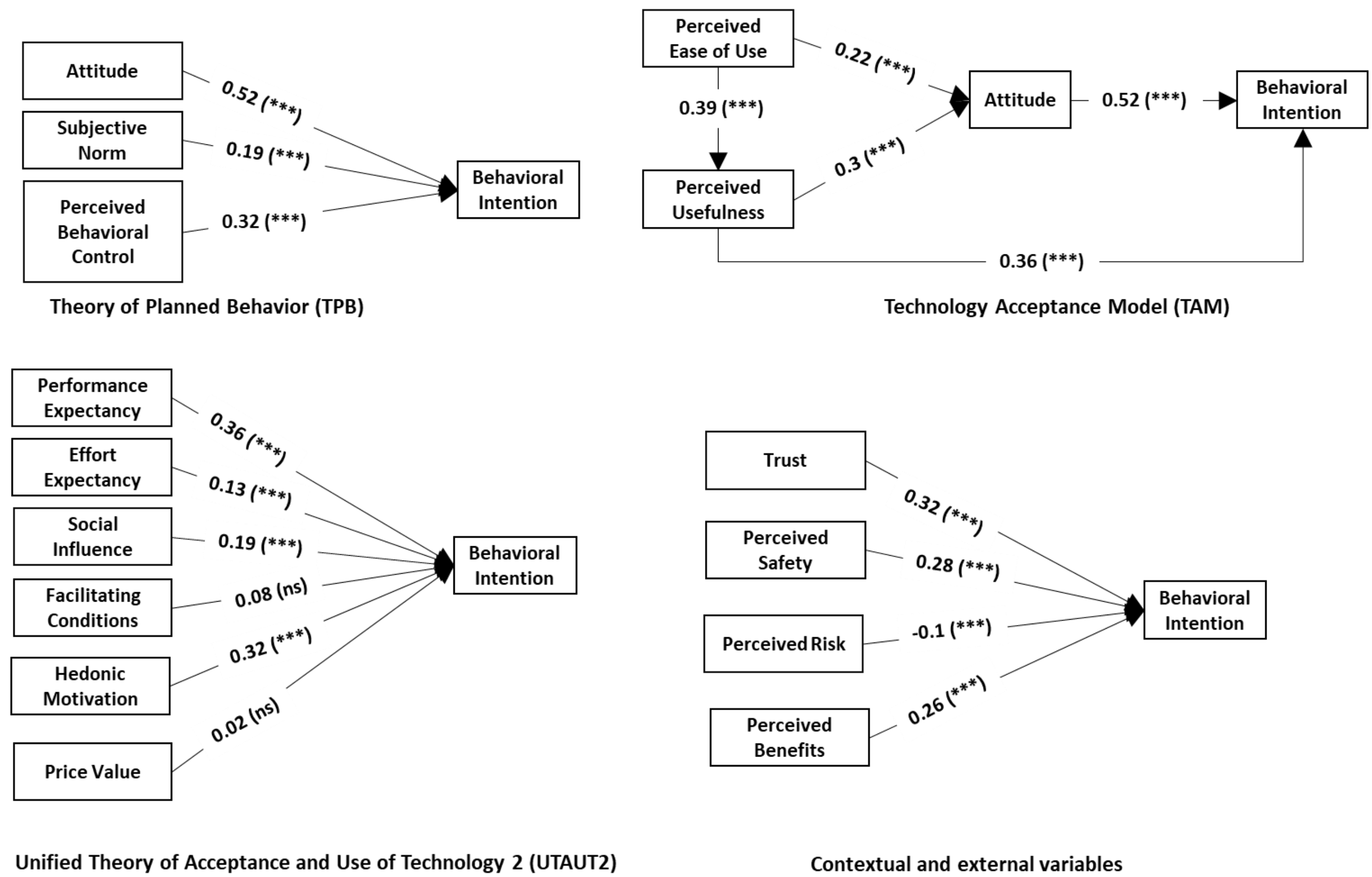

Fig.4 Meta-analytic results - theoretical view

5.4 Reliability estimation

Combined reliability estimates have been used to establish the consistency of the variables included in the research model (Zhao et al., 2018). Cumulative estimates were calculated from the reliability statistics (i.e., Cronbach alpha and composite reliability) obtained from individual studies. Reliability estimates were calculated using the Cronbach alpha mainly. When the Cronbach alpha was not available for a particular study, we used the composite reliability. We must note that a few studies have reported neither the Cronbach alpha nor the composite reliability. Table 5 presents the summary of the reliability statistics for the 13 variables included in the research model. Average reliability of all constructs included in the model ranged from 0.839 to 0.913. Higher reliability values exceeding the recommended threshold of 0.7 confirm the robustness and consistency of the constructs and their applicability in the context of AVs.

Table 5: Combined reliability estimates

Construct	No. of studies	Range	Average	Variance
BI	55	0.71-0.98	0.905	0.004
PU	37	0.75-0.95	0.870	0.003
TRU	25	0.75-0.99	0.903	0.004
PEOU	35	0.68-0.99	0.877	0.005
ATT	17	0.82-0.97	0.907	0.002
SI	23	0.7-0.97	0.839	0.009
HM	9	0.75-0.96	0.886	0.006
PRI	8	0.83-0.95	0.899	0.001
PSAF	6	0.8-0.9	0.867	0.001
PBEN	6	0.85-0.91	0.888	0.000
PBC	5	0.72-0.95	0.846	0.001
PREV	5	0.88-0.94	0.913	0.001
FC	5	0.79-0.89	0.842	0.001

5.5 Moderator analysis – Level of automation

Heterogeneity analysis revealed high variations in the outcomes of the studies that investigated the relationship between the antecedents of intention to use AVs. High heterogeneity signaled the need to investigate the lurking or exogenous variables to understand the reason behind the variability (Jadil et al., 2021). Thus, we considered the situational moderators' level of automation, vehicle ownership and culture for gaining a deeper understanding of the variability.

Table 6 shows the results of the moderator analysis on the level of automation. Sub-group differences of Level 3 and Levels 4 and 5 were assessed for the nine hypothesized relationships. Only the relationships investigated in at least two studies by both the groups were considered for moderator analysis. For instance, the relationship between perceived safety and behavioral intention, which was not investigated in two studies based on Level 3 automation, has not been included in the analysis. Similarly, six such paths that did not meet the eligibility criteria were not considered for the analysis. Result of the moderator analysis performed using level of automation revealed significant subgroup differences for five paths, i.e., perceived usefulness → behavioral intention, trust → behavioral intention, attitude → behavioral intention, social influence → behavioral intention, and perceived ease of use → attitude. The remaining four paths were not supported in our analysis. Thus, the moderating role of the level of automation (H13) is partially supported.

Table 6: Moderator Analysis (Level 3 Vs Level 4&5)

Relationship	Group	Number of Studies	Combined effect size	95% Confidence interval		Q-value (Between)	p-value
				Lower	Upper		
PU - BI	L3	5	0.121	0.102	0.140	58.626	0.000
	L4&L5	16	0.373	0.350	0.395		
TRU - BI	L3	5	0.254	0.207	0.300	49.409	0.000
	L4&L5	10	0.439	0.413	0.464		
PEOU - PU	L3	3	0.328	0.273	0.381	0.296	0.587
	L4&L5	7	0.310	0.275	0.345		
ATT - BI	L3	3	0.633	0.579	0.682	28.110	0.000
	L4&L5	8	0.459	0.431	0.486		
PEOU - BI	L3	4	0.088	0.069	0.108	0.363	0.565
	L4&L5	12	0.122	0.093	0.150		
SI - BI	L3	3	0.381	0.364	0.397	23.905	0.000
	L4&L5	10	0.165	0.132	0.198		
PU - ATT	L3	2	0.303	0.217	0.385	0.725	0.395
	L4&L5	2	0.350	0.281	0.415		
PEOU - ATT	L3	2	0.060	-0.032	0.152	7.395	0.007
	L4&L5	2	0.224	0.150	0.295		
PBEN - BI	L3	2	0.170	0.091	0.247	0.891	0.345
	L4&L5	2	0.220	0.150	0.288		

5.6 Moderator analysis – Vehicle ownership

This study envisaged that vehicle ownership could play a catalytic role. Thus, the moderating role of vehicle ownership was examined for the hypothesized relationships. Table 7 presents the result summary of the moderator analysis on vehicle ownership. Ten out of fifteen paths that met the eligibility criteria have been included in the study. The remaining five paths did not qualify for the moderator analysis. The result of the moderator analysis performed for vehicle ownership revealed significant subgroup differences for seven paths, i.e., perceived usefulness → behavioral intention, trust → behavioral intention, attitude → behavioral intention, social influence → behavioral intention, perceived ease of use → attitude, hedonic motivation → behavioral intention, and facilitating condition → behavioral intention. The remaining three paths were not supported in our analysis. Thus, the moderating role of vehicle ownership (H6) is partially supported.

Table 7: Moderator Analysis (Public vs. Private)

Relationship	Group	Number of Studies	Combined effect size	95% Confidence interval		Q-value (Between)	p-value
				Lower	Upper		
	Private	16	0.356	0.327	0.385		
PU - BI	Public	9	0.222	0.206	0.237	60.689	0.000
	Private	6	0.323	0.277	0.368		
TRU - BI	Public	4	0.102	0.047	0.157	36.015	0.000
	Private	6	0.556	0.520	0.591		
PEOU - PU	Public	4	0.571	0.532	0.608	0.316	0.574
	Private	7	0.593	0.572	0.612		
ATT - BI	Public	6	0.334	0.290	0.377	128.013	0.000
	Private	10	0.353	0.337	0.368		
SI - BI	Public	9	0.152	0.112	0.193	86.927	0.000
	Private	15	0.100	0.084	0.115		
PEOU - BI	Public	6	0.128	0.088	0.167	1.699	0.192
	Private	2	0.271	0.230	0.312		
PU - ATT	Public	4	0.221	0.167	0.273	2.205	0.138
	Private	2	0.050	0.006	0.094		
PEOU - ATT	Public	4	0.369	0.320	0.417	86.104	0.000
	Private	4	0.490	0.474	0.505		
HM - BI	Public	4	0.357	0.306	0.407	26.791	0.000
	Private	4	-0.077	-0.096	-0.058		
FC - BI	Public	2	0.257	0.182	0.328	68.000	0.000

5.7 Moderator Analysis Culture

The moderating impact of culture was investigated for ten of the hypothesized relationships that qualified for the sub-group analysis. Summary of the sub-group differences between the eastern and western cultures is shown in Table 8. Results of the moderator analysis revealed that the sub-group differences were significant for seven relationships. Moderator analysis distinguished the antecedents of behavioral intention to use AVs across eastern and western cultures. For five out of the seven significant relationships, perceived ease of use → perceived usefulness, perceived ease of use → attitude, perceived ease of use → behavioral intention, social influence → behavioral intention, and trust → behavioral intention, eastern culture had a significantly high effect size compared to western cultures. The remaining two relationships, attitude → behavioral intention, and hedonic motivation → behavioral intention, were stronger in western cultures as compared to eastern cultures.

Table 8: Moderator Analysis (Culture)

Relationship	Group	Number of Studies	Combined effect size	95% Confidence interval		Q-value (Between)	p-value
				Lower	Upper		
PU - ATT	Eastern	4	0.280	0.232	0.326	0.020	0.888
	Western	5	0.284	0.248	0.319		
PU - BI	Eastern	13	0.350	0.326	0.374	0.674	0.412
	Western	29	0.312	0.300	0.324		
PEOU - PU	Eastern	10	0.457	0.431	0.493	5.261	0.022
	Western	12	0.331	0.301	0.361		
PEOU - ATT	Eastern	4	0.304	0.257	0.349	45.050	0.000
	Western	5	0.095	0.057	0.133		
PEOU - BI	Eastern	10	0.216	0.173	0.239	12.324	0.000
	Western	25	0.107	0.058	0.116		
SI - BI	Eastern	9	0.365	0.351	0.389	18.503	0.000
	Western	18	0.232	0.190	0.273		
TRU - BI	Eastern	14	0.357	0.323	0.370	33.740	0.000
	Western	11	0.216	0.192	0.260		
PSF - BI	Eastern	2	0.241	0.186	0.294	2.846	0.094
	Western	5	0.321	0.307	0.343		
ATT - BI	Eastern	8	0.435	0.405	0.464	295.167	0.000
	Western	12	0.685	0.673	0.697		
HM - BI	Eastern	2	0.245	0.165	0.321	32.356	0.000
	Western	9	0.460	0.445	0.474		

6. Discussion

Inconsistent outcomes reported on the antecedents of AV adoption have masked the generalizability of the findings. In the AVs context, contradictions emanated from the deployment of complementary and competing theoretical perspectives, mixed findings reported for the same relationships, and large variability in the strength of associations reported across the studies. The purpose of this study was to reconcile the inconsistencies and establish the relative importance of the dominant relationships between the antecedents of behavioral intention to use AVs and the moderators, with an effort to advance the theory and practical knowledge in this fast-emerging phenomenon. This research synthesized 65 empirical studies published in 58 articles with a cumulative sample size of 37,076. The findings of this meta-analytic study supported most of the hypothesized relationships, except the impact of facilitating conditions and price value on the intention to use AVs; and ascertained the significance of technological, individual, and security (TIS) dimensions in adopting AV technologies.

Technology is the key driver of the development of AVs. A set of hypotheses (H1a-H4) proposed that the technological factors significantly impact the behavioral intention to adopt AVs.

Hypotheses H1a proposed the relationship between perceived usefulness on behavioral intention to use AVs - this was supported. Among the technological factors, perceived usefulness emerged as strongest determinants of intention. This result is consistent with the prior studies (Kapser & Abdelrahman, 2020; Panagiotopoulos & Dimitrakopoulos, 2018). Hypothesis H1b proposed the relationship between perceived usefulness and attitude - this was supported in our result. Our results revealed that the usefulness of the AV technology in enhancing performance, safety, fuel efficiency, and improved traffic conditions is crucial for shaping attitude and behavior (Baccarella et al., 2020). Hypothesis H2a proposed the relationship between perceived ease of use on behavioral intention. Extant research revealed conflicting results on the hypotheses H2a. While half of the studies found perceived ease of use as significant (Wu et al., 2019; Bernhard et al., 2020), the rest reported non-significant relationships (Kapser & Abdelrahman, 2020; Jing et al., 2021). By reconciling the inconsistencies, our analysis supported hypothesis H2a. Our findings revealed perceived ease of use as a significant predictor of intention to use AVs with a small effect size. Perceived ease of use emerged as a significant predictor of perceived usefulness and attitude. Thus, hypotheses H2b and H2c were supported. Our results posited that effortless use of AVs would enable users to discover the maximum utility of the vehicle and lead to a positive attitude and behavior towards AV use (Baccarella et al., 2020). Hypothesis H3 proposed the relationship between facilitating condition and behavioral intention to use AVs. Conflicting results were reported for this relationship. The impact of facilitating condition on behavioral intention is not supported in our analysis. This result is consistent with the prior studies on AV adoption (Nordhoff et al., 2020a). Most of the study sample consisted of individuals with a functional understanding of AVs or those who have experienced AVs in a controlled environment. Once the AVs hit the public roads in a larger scale, it would be possible for users to realize the need for infrastructure and other facilities. Therefore, future studies should constantly explore the impact of facilitating conditions on the AV adoption. Hypothesis H4 proposed a significant positive influence of social influence on the behavioral intention to use AVs. Mixed results have been reported for the relationship between social influence and behavioral intention (Dai et al., 2021; Kaye et al., 2020). However, our findings support H4. Meta-analytic findings from our study revealed social acceptance and the opinion of important social members (i.e., friends, family, colleagues) as significant drivers of AV adoption.

Individual context influenced by peoples' working style and lifestyle have a significant bearing on technology adoption (Hung et al., 2014). This study investigated the impact of individual differences on the intention to use AVs. Hypothesis H5 proposed the relationship between attitude and the behavioral intention - this was supported in our analysis. Attitude is the most investigated individual construct, which also emerged as the strongest determinant of behavioral intention. This result is aligned with (Chen, 2019), who revealed that a positive attitude towards AVs translates into people accepting them in the near future. Our analysis also revealed that the utility of AVs (perceived usefulness) and ease of use are vital factors for generating a positive attitude among individuals. The link between attitude and behavior is firmly established in the context of AVs. Hypotheses H6 and H7 proposed that hedonic motivation and perceived benefits significantly impact the behavioral intention to use AVs. Both hedonic motivation and perceived benefits had a moderate impact on behavioral intention, supporting H6 and H7. The ability of fully AVs to facilitate passengers in engaging with various entertainment and fun related activities while commuting are factors which would make the travel enjoyable and encourage user acceptance (Kapser & Abdelrahman, 2020). The study also revealed that perceived benefits accrued from adopting AVs with respect to time-saving, fuel-saving, space-saving, and other environmental benefits would also promote AV acceptance (Manfreda et al., 2021). Hypotheses H8 proposed the relationship between the price evaluation and behavioral intention - this is not supported in our analysis. Even though price evaluation had a positive impact on behavioral intention, this result was surprising as prior studies have indicated pricing could affect the acceptance of AVs (Herrenkind et al., 2019a; Seuwou et al., 2020). Two plausible reasons can be attributed to the non-significant impact of price evaluation - first, prior studies have revealed low impact sizes for the effects of price evaluation on AV use intention; second, given that the AVs are loaded with advanced sensors, automated controls, and intelligent navigation systems, there is a willingness among the potential consumers to accept AVs when the price is comparable to conventional vehicles (Nastjuk et al., 2020). Hypothesis H9's proposal that there is a significant relationship between perceived behavioral control and behavioral intention to use AVs, found support in our analysis. The tendency of the individuals to retain control over the vehicles was found to be a significant predictor of AV acceptance. Prior studies have posited that participants were assertive that they could operate the AVs when they become commercially available (Kaye et al., 2020; Yuen et al., 2020c).

Autonomous vehicles transfer the decisions involving life and death to the machines (Awad et al., 2018; Dwivedi et al., 2021). Security in AVs, both physical security and cyber security, are crucial factors for the success of AVs. If there is one aspect that can hamper the pace of diffusion of autonomous vehicles, it would be none other than the perceived security. This study has investigated the impact of security factors on the intention to use AVs. Hypothesis H10 and H11 proposed that trust and perceived safety significantly positively impacted behavioral intention to use AVs. Hypothesis H12 proposed that perceived risk had a significant negative impact on behavioral intention. Our results established trust, perceived safety, and perceived risk as significant predictors of intention to use AVs. Thus, hypotheses H10-H12 were supported. This result is in line with the prior studies (Manfreda et al., 2021; Koohang et al., 2022; Du et al., 2021). Trust emerged as the strongest security factor followed by perceived safety. As expected, the combined effect size of perceived risk was negative. Our findings demonstrated that the security aspect of AVs could be enhanced through credible system performance coupled with improved safety features and appropriate risk mitigation strategies to deal with physical, functional, and privacy risks (Jing et al., 2021).

High heterogeneity across the investigated relationships prompted us to investigate the potential contextual moderators and espoused culture. Thus, the present study investigated the contextual moderators: level of automation and vehicle ownership. Hypothesis H13 proposed that the level of automation has a moderating impact on the antecedents of the behavioral intention to use AVs. The results confirmed the moderating impact of five out of nine relationships investigated. Hypothesis H13 was partially supported. Sub-group differences were observed for three key determinants of the intention to use AVs: perceived usefulness, trust, and attitude. Firstly, perceived usefulness had a low impact for the limited automation (L3) and a moderate impact for the high and full automation (L4 & L5). Our study found that usefulness of AVs perceived by the individuals is increasing, along with the increasing levels of automation. Secondly, trust revealed a pattern similar to that of perceived usefulness. Respondents bestowed higher trust on the AVs with higher automation. Thirdly, sub-group differences were observed for the relationship between attitude and intention. Here, the effect size of controlled automation is significantly larger than that of high automation. Even though the coefficient is high for both categories, manufacturers should take concerted efforts to generate a positive attitude towards highly automated and fully autonomous AVs. Fourthly, we observed sub-group differences for the relationship between social influence and behavioral intention. Controlled automation had higher effect size than high automation. Commercial availability of fully autonomous vehicles in the near future might moot the social discussion and is expected to pave the way for social influence to have a higher impact on the intention to use (Dai et al., 2021).

Hypothesis H14 proposed the moderating impact of vehicle ownership on the antecedents of the behavioral intention to use AVs. The result of the moderating analysis revealed the moderating impact of seven out of the ten relationships investigated. Thus, hypothesis H14 is partially supported. The results indicated the stark differences in the relationship between the antecedents of intention to use AVs. Sub-group differences were observed for constructs that are crucial for the adoption of AVs, i.e., perceived usefulness, attitude, trust, social influence, and hedonic motivation. For all the above constructs, the impact size of private AVs was significantly higher than that of public AVs. There seem to be fewer incentives for the public to accept technologies (Wang et al., 2021). For instance, an autonomous public bus is no different from a traditional bus. Therefore, creating some incentive mechanisms and informing public transport users about the larger benefits to society and the environment as-a-result of adopting AVs should be considered. This result is aligned with that of Liu et al. (2019), who argued that the public perception of AVs will range from neutral to negative during the early stage of development. Differences in the enjoyment options (hedonic motivation) pursued by the private and public AVs are expected. However, the differences in utility, trust and social perception are surprising. Our analysis shows the reluctance among individuals to visualize AVs as public vehicles (Yuen et al., 2020b). Public adoption is vital for AV technology to reach the critical masses and the society to realize the full benefits of AVs. Sub-group differences observed in the study call for the AV manufacturers' and the governments' coordinated actions to create favorable conditions for shaping the public perception and acceptance of autonomous vehicles.

Hypothesis H15 proposed that the espoused culture significantly moderates the relationship between the antecedents of the behavioral intention to use AVs. Culture had a significant influence on seven out of the ten relationships investigated. Thus, hypothesis H15 is partially supported. The impact of perceived usefulness on attitude and behavioral intention is insignificant both in eastern and western cultures. The relationship between perceived safety and behavioral intention is not statistically different between the eastern and western cultures. However, the effect size was slightly higher in western cultures. The impact of perceived ease of use on attitude, perceived usefulness and behavioral intention is significantly moderated by the culture. The impact of perceived ease of use on behavioral intention is stronger in eastern cultures. Two plausible reasons can be attributed to this result. Firstly, highly motorized western cultures possess high resource availability and they also witness continuous development of automobiles (Wang et al., 2020). The tendency to try out developing or new technologies is high in western cultures (Mehta et al., 2021). This explains the low importance given to the perceived ease of use of the AV technology in western culture. Secondly, eastern cultures are less motorized, wherein automobile ownership is relatively less. Moreover, the emphasis in eastern cultures is quality of life. Thus, perceived ease of use plays a significant role in eastern cultures (Jing et al., 2021; Zhu et al., 2020). The relationship between social influence and behavioral intention is stronger in eastern cultures (Zhang et al., 2020). This result is aligned with the findings from previous meta-analytical studies on technology adoption (Zhao et al., 2021; Gopinath et al., 2021). The impact of trust on behavioral intention is stronger in eastern cultures. The attitude-behavior link was found to be dominant in western cultures (Mojaverian et al., 2013). Further, the hedonic motivation to adopt AVs was stronger in western cultures. High self-esteem and the motivation to uphold the self-image among the westerners (Brown et al., 2009) could be attributed as key reasons.

6.1. Theoretical implications

By systematically reviewing the existing empirical studies on the AV adoption literature, this research identified the dominant constructs, framed the overarching conceptual model based on the TIS (technology, individual, and security factors) dimension, tested the conceptual model and the contextual moderators using meta-analytical principles; established the combined effect size for the dominant relationships by reconciling the inconsistencies, and study aptly addressed the calls for the quantitative synthesis (Jing et al., 2020; Bornholt & Heidt, 2020) of the rapidly evolving AV adoption literature. This study makes several important contributions to AV literature.

First, several technology acceptance theories and contextual factors have been used in the context of AVs. While several theories (i.e., TPB, TAM, UTAUT, and DOI) have been used to explore AV adoption (Golbabaei et al., 2020), there is a paucity of research to quantitatively synthesize and create a holistic perspective on AV adoption. The conceptual model tested in this study utilized the key relationships from TPB, TAM, and UTAUT and established the consistency, robustness, and applicability of these theories in the context of AVs. The theoretical view outlined in Fig.4 shows the direction and combined magnitude of the theoretical relationships and contextual variables investigated in the adoption of AVs. The holistic perspective generated in the study can act as a common foundation for future studies on AV adoption. Findings from this research can aid the scholars in making an informed selection of the constructs for future studies.

Second, from an extensive review of the literature on AVs, this study has developed a holistic conceptual model for the adoption of AV technology. We propose that TIS factors have a significant bearing on the future acceptance of AVs. Weight analysis performed in the study discovered inconsistent findings for the three paths. Conflicting findings were reported for the relationships between perceived ease of use, facilitating condition, perceived risk, and the behavioral intention to use AVs. Our meta-analysis results found support for 13 of the 15 relationships investigated. Based on the magnitude of the relationships, six constructs have been identified as best predictors of AV adoption. These constructs include attitude, perceived usefulness, trust, hedonic motivation, perceived safety, and social influence. Perceived risk is the only variable with a significant adverse effect on the intention to use AVs. Overall, meta-analytic findings from this study brings a measure of clarity regarding the inconsistent conclusions and generalizability of the relationships essential for AV adoption.

Thirdly, this study was a pioneering effort to shed light on the moderating impact of the level of automation, vehicle ownership and culture in AV adoption. By segregating the studies based on the automation levels and the vehicle ownership, and further subjecting them to moderator analysis, this study has revealed the relationships affected by the moderators. With respect to the level of automation, the impact of perceived usefulness, trust, and social influence was found to increase with the increase in automation. However, the impact of attitude on behavioral intention is slightly lower for the high and full automation. AV technology's development and widespread commercialization requires several years (Liu et al., 2019a). The attitude towards behavioral intention is expected to slowly improve when more and more people are exposed to AVs' rewarding experiences (Dai et al., 2021). The moderating impact of vehicle ownership demonstrated the low effect of public transport on perceived usefulness, trust, attitude, effort expectancy, and social influence, as compared to that of private transport.

This study is a maiden attempt to unleash the moderating impact of culture in the context of AVs. By splitting the empirical studies into eastern and western cultures, this study demonstrated how cultural values influence the antecedents of AV adoption. Findings from the study revealed the distinct cultural effect of perceived ease of use, social influence, trust, attitude, and hedonic motivation on the behavioral intention to use AVs. The study findings widen the body of knowledge on AV literature by providing evidence on the impact of cultural anchors in AV technology adoption. Moderator analysis on culture offered critical insights for the multinational promotion of AVs. AV technology is not yet commercially available across the nations. Participants included in several studies were only aware of the AV concept. Most of the participants lack experience with AVs. Future studies can investigate the variations caused by cultural anchors when the AVs become a commercial reality. By quantitatively synthesizing the existing literature on AV adoption, the present study can act as guidepost for future investigations in choosing the appropriate constructs.

6.2. Practice and policy implications

Quantitative synthesis of a substantial body of literature pertaining to AV technology removes the bias from specific studies and leaves the consolidated statistical evidence for the practitioners and policymakers to act upon.

This study shows that technical factors such as perceived usefulness, ease of use, and social influence have a significant impact on AV adoption intention. Manufacturers should invest in introducing new features in the AVs. Simultaneously, mass media should be effectively used to inform people about the usefulness and the benefits of embracing the novel AV technology. Even though perceived ease (or effort expectancy) of use had a low impact, effort should be made to enhance the conveniences by minimizing the cognitive effort required to operate AVs. This study has showed the significant effect of social factors such as social influence and subjective norm in promoting AV adoption intention. Thus, practitioners should undertake advertising campaigns and organize social events to garner positive social perceptions about AVs.

The meta-analysis highlighted the vitality of security dimensions (i.e., safety, risk, and trust). Manufacturers should employ a 3-point strategy to enhance the security perspectives. Firstly, safety vulnerabilities should be critically examined, and safety systems should be enhanced. Secondly, more participants should be made to experience the ride and safety aspects built into the AVs (Zhu et al., 2020). A rewarding experience with the AVs can lower the negative risk perception and build public trust. Thirdly, manufacturers should actively utilize mass media and social media to spread the utility, benefits, safety systems, and recent developments in AV technology.

Moderator analysis unraveled the significant differences in the usefulness of AVs perceived in terms of public and private transport. Moreover, public reluctance is evident from the low impact on the relationship between the antecedents of behavioral intention. Public acceptance is crucial for the broader deployment of AVs. Government should play a catalytic role along with the AV manufacturers in creating awareness, promoting usefulness, and enabling the development of AVs. Governments should establish a political goal with respect to the pace at which they want to implement the AV deployment; and more importantly, develop a policy for integrated autonomous cum electric vehicle implementation (Wu et al., 2019). Clearly, a coalition should be formed between the government and AV manufacturers to create favorable conditions for public acceptance and use.

The moderating impact on culture necessitates that differential strategies must be adopted in the design, development and promotion of AVs in eastern and western cultures. Firstly, perceived ease of use had the significant bearing on the adoption of AVs in eastern cultures. Thus, ease of use should be seriously considered while introducing AVs in eastern cultures. Secondly, social influence plays a vital role in the collectivist eastern cultures. Thus, manufacturers of AVs should organize road shows, recruit brand ambassadors, run awareness programs, and float social media campaigns in eastern countries to win the confidence of the collectivist societies. Impact on trust was stronger in eastern cultures and perceived safety was stronger in western cultures. There should not be any compromise on the safety systems in AVs. However, findings revealed the significance of trust in eastern cultures. Trust building activities should be given due importance in the collectivist eastern cultures. The attitude-behavior link and the hedonic motivation-behavior link were both stronger in western cultures. Introducing advanced driving features, educating people on the utility of AVs and creating pleasant driving experiences (Bernhard et al., 2020) can enhance hedonic motivation and boost a positive attitude towards AV adoption.

6.3. Limitations and avenues for future research

Like any empirical research, the current study has some limitations which provide directions for further research. One of the inherent limitations is that meta-analysis cannot be a primary study in itself; instead, the quantitative synthesis should guide future research (Eisend & Tarrahi, 2021). Although utmost care was taken in selecting the articles, studies that fail to meet the inclusion criteria were not part of the analysis. Another limitation relates to the study selection. The current study has not considered dissertations and unpublished reports in calculating the combined effect size, which we recommend to be accounted in future research. The TIS framework proposed in the study could be empirically tested using primary empirical investigations. We investigated the moderating impact of the level of automation, vehicle ownership and culture that are vital for the diffusion of AVs; we further assumed that the mean age of the study samples included in the meta-analysis is representative. However, this assumption cannot hold good in all circumstances. Thus, future meta-analysis studies on AV adoption could investigate the moderating impact of age and gender. Further, we examined the cultural differences across the eastern and western cultures. Future studies could consider how each of the four cultural dimensions of Hofstede's influences the adoption of AVs (Wong & Cheng, 2020).

The findings of our study provide the quantitative synthesis of the frequently studied variables emanating from popular technology adoption theories. Future studies on AV adoption could develop conceptual models incorporating contextual variables such as driving pleasure, car necessity, and psychological ownership. Future studies should promote ethical dialogues regarding the use of AVs. Ethical considerations governing the responsibility for the unavoidable accidents caused by AVs are lacking in the literature (Karnouskos, 2020a). To address this shortfall, we recommend future studies to develop ethical frameworks (Ashok et al., 2022) and decision algorithms concerning unavoidable accidents by autonomous agents. Further, the role of government support and incentives in AV adoption merits scholarly attention. Studies on autonomous electric vehicles (AEV) should focus on understanding the impact of driving range and access to charging stations on the adoption of AEVs. AV technology is developing very fast, and so are the adoption studies. Thus, we encourage scholars to update our meta-analysis with newer studies in the next five to ten years' time frame.

7. Conclusion

This study synthesized 65 studies (k=65, N= 37,076) drawn from AV adoption literature, and used meta-analysis to enhance our understanding of the magnitude of the relationship between the critical antecedents of behavioral intention. We adopted the TIS framework for the analysis, and investigated technology factors (perceived usefulness, perceived ease of use, facilitating condition, and social influence), individual factors (attitude, hedonic motivation, perceived benefits, price evaluation, and perceived behavioral control) and security factors (trust, perceived safety, and privacy risk). Our findings indicate that AV adoption is moderated by the level of automation, vehicle ownership and culture. The theoretical model validated in this study will inform the researchers on AV adoption and will guide them in selecting constructs for future research. Insights from the moderator analysis on level automation can aid practitioners in strategy formulation, and those on the differing impacts on vehicle ownership would play a critical role in policy formulation. Cultural differences can aid in the multinational development of AVs.

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Appendix 1. Study characteristics

Author & Year	Source	Sample size	Country	Culture	Level of automation	Ownership	Article Types	Theories used
Jing et al., 2021	Accident Analysis and Prevention	340	China	Eastern	SAE Level 5	General	J	Extended TAM
Dai et al., 2021	Accident Analysis and Prevention	117	China	Eastern	SAE Level 4	Public	J	Extended TPB
Du et al., 2021	Travel Behaviour and Society	173	China	Eastern	SAE Level 5	Private		SCT
Winter et al., 2020	J. of Air Transport Management	510	US	Western	Not assigned	General	J	-
Hryniewicz & Grzegorczyk, 2020	PLoS ONE	303	Poland	Western	Not assigned	Private	J	TAM, Agency and communication theory
			Poland	Western	Not assigned	Private	J	
Karnouskos, 2020a	IEEE Transactions on Engineering Management	126	Sweden	Western	Not assigned	Private	J	Ethical frameworks
Baig & Mir, 2020	J. of Advanced Research in Dynamical and Control Systems	384	Malaysia	Eastern	Not assigned	Private	J	-
Yuen et al., 2020d	International J. of Sustainable Transportation	676	China	Eastern	SAE 4 and above	General	J	HBM, trust theory
Nastjuk et al., 2020	Tech. Forecasting and Social Change	316	Germany	Western	SAE Level 5	General	J	Extended TAM
Feys et al., 2020	Sustainability	384	Belgium	Western	Not assigned	Public	J	UTAUT
		145	Belgium	Western	Not assigned	Public	J	UTAUT
Dirsehan & Can, 2020	Technology in Society	391	Turkey	Western	SAE Level 5	General	J	Extended TAM
Yuen et al., 2020e	J. of Cleaner Production	526	Korea	Eastern	SAE 4 and above	General	J	IDT
Nordhoff et al., 2020a	Transportation Research Part F: Traffic Psychology and Behaviour	9118	8 European countries	Western	SAE Level 3	Private	J	UTAUT
Erskine et al., 2020	J. of Consumer Marketing	374	US	Western	Not assigned	General	J	UTAUT2
Zhu et al., 2020	Transportation Research Part F: Traffic Psychology and Behaviour	355	China	Eastern	SAE Level 5	Public	J	TAM, TPB and UTAUT
Yuen et al., 2020c	International J. of Environmental Research and Public Health	268	Vietnam	Eastern	Not assigned	Public	J	UTAUT2 and TPB
Yuen et al., 2020b	International J. of Environmental Research and Public Health	526	Korea	Eastern	SAE 4 and above	General	J	Extended TPB
Bernhard et al., 2020	Transportation Research Part F: Traffic Psychology and Behaviour	942	Germany	Western	Not assigned	Public	J	UTAUT
Zhang et al., 2020	Transportation Research Part C: Emerging Technologies	604	China	Eastern	SAE Level 3	General	J	Extended TAM
Kaye et al., 2020	Accident Analysis and Prevention	558	Australia	Western	SAE Level 4	Private	J	TPB and UTAUT
		625	France	Western	SAE Level 4	Private	J	TPB and UTAUT
		380	Sweden	Western	SAE Level 4	Private	J	TPB and UTAUT

Kapser & Abdelrahman, 2020	Transportation Research Part C: Emerging Technologies	501	Germany	Western	Not assigned	General	J	UTAUT2
Bruckes et al., 2019	Proc. ECIS'19	286	Germany	Western	Not assigned	General	C	TAM and Trust
Man et al., 2020	IEEE Access	237	Hong Kong	Western	SAE Level 3	General	J	TAM
Morrison & Belle, 2020	Proc. ICCDS'20	441	South Africa	Eastern	Not assigned	General	C	UTAUT
Liu et al., 2020	J. of Advanced Transportation	454	China	Eastern	Not assigned	Private	J	UTAUT
Karnouskos, 2020b	Cognition, Technology and Work	62	Germany	Western	Not assigned	Private	J	-
Baccarella et al., 2020	European J. of Innovation Management	324	Germany	Western	SAE Level 5	General	J	TAM
Seuwou et al., 2020	Advances in Intelligent Systems and Computing	408	UK	Western	Not assigned	General	C	UTAUT2
Yuen et al., 2020a	Technology Analysis and Strategic Management	274	China	Eastern	SAE Level 5	General	C	TAM
Nordhoff et al., 2020b	Theoretical Issues in Ergonomics Science	315	Greece	Western	Not assigned	Public	J	UTAUT
Koul & Eydgahi, 2019	Periodica Polytechnica Transportation Engineering	377	US	Western	Not assigned	General	J	TPB
Montoro et al., 2019	Safety Science	1205	Spain	Western	Not assigned	Private	J	-
Hegner et al., 2019	International J. of Human-Computer Interaction	369	Germany	Western	SAE Level 5	Private	J	Extended TAM
Herrenkind et al., 2019a	Transportation Research Part D: Transport and Environment	268	Germany	Western	Not assigned	Public	J	Extended TAM
Rahman et al., 2019	Transportation Research Part F: Traffic Psychology and Behaviour	173	US	Western	SAE Level 5	General	J	TPB and TAM
Liu et al., 2019	International J. of Human-Computer Interaction	367	China	Eastern	SAE Level 4	General	J	-
		375	China	Eastern	SAE Level 5	General	J	-
Liu et al., 2019a	Transportation Research Part A: Policy and Practice	300	China	Eastern	SAE Level 3	General	J	Trust heuristic and affect heuristic
		300	China	Eastern	SAE Level 3	General	J	Trust heuristic and affect heuristic
Liu et al., 2019b	Risk Analysis	441	China	Eastern	Not assigned	Private	J	Trust heuristic
Manfreda et al., 2021	International J. of Information Management	382	Slovenia		Not assigned	General	J	-
Chen, 2019	Transportation Research Part F: Traffic Psychology and Behaviour	700	Taiwan	Eastern	Not assigned	Public	J	TAM
Lee et al., 2019a	Transportation Research Part C: Emerging Technologies	313	Korea	Eastern	Not assigned	General	J	Extended TAM
Herrenkind et al., 2019b	Transportation Research Part D: Transport and Environment	116	Germany	Western	Not assigned	Public	J	Extended TAM
		152	Germany	Western	Not assigned	Public	J	Extended TAM
Kettles & Van Belle, 2019	Proc. icABCD'19	121	South Africa	Eastern	Not assigned	Private	C	UTAUT

Müller, 2019	Sustainability	1177	Europe, China and North America	NA	Not assigned	General	J	Extended TAM
Sener et al., 2019	Transportation Research Part F: Traffic Psychology and Behaviour	3097	US	Western	Not assigned	General	J	CTAM
Lee et al., 2019c	Multimodal Technologies and Interaction	158	US	Western	Not assigned	Private	J	TAM
Wu et al., 2019	Transportation Research Part F: Traffic Psychology and Behaviour	470	China	Eastern	Not assigned	General	J	TAM
Zhang et al., 2020	Transportation Research Part C: Emerging Technologies	216	China	Eastern	SAE Level 3	Private	J	Extended TAM
Xu et al., 2018	Transportation Research Part C: Emerging Technologies	300	China	Eastern	SAE Level 3	Private	J	Extended TAM
Panagiotopoulos & Dimitrakopoulos, 2018	Transportation Research Part C: Emerging Technologies	483	Europe	Western	Not assigned	General	J	Extended TAM
Buckley et al., 2018	Accident Analysis and Prevention	74	US	Western	SAE Level 3	Private	J	TAM and TPB
Koul & Eydgahi, 2018	J. of Technology Management and Innovation	377	US	Western	Not assigned	Private	J	TAM
Leicht et al., 2018	J. of High Technology Management Research	241	France	Western	SAE Level 5	Private	J	UTAUT
Ernst & Reinelt, 2017	Proc. AMCIS'17	100	Germany	Western	SAE Level 5	Private	C	Extended TAM
Lee et al., 2017	LNCS'17	1765	US	Western	Not assigned	Private	C	Extended TAM
Madigan et al., 2017	Transportation Research Part F: Traffic Psychology and Behaviour	315	Greece	Western	SAE Level 4	Public	J	UTAUT
Madigan et al., 2016	Transportation Research Procedia	349	France and Switzerland	Western	SAE Level 4	Public	C	UTAUT
Choi and Ji, 2015	International J. of Human-Computer Interaction	552	Korea	Eastern	SAE Level 5	General	J	Extended TAM

Note: TAM - Technology acceptance model; CTAM - Car TAM; UTAUT - Unified theory of acceptance and use of technology; UTAUT2 - Extended UTAUT; TPB - Theory of planned behavior; IDT - Innovation diffusion theory; HBM – Health belief model; SCT – Social cognitive theory; J – Journal, C – Conference proceeding/book chapter.

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