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Behavioural intention to use autonomous vehicles: Systematic review and empirical extension

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ABSTRACT

This study aims to enrich autonomous vehicle (AV) adoption research and practice by being the first study to systematically review empirical studies on behavioural intention to use AVs, a key element in the adoption process. This review of the extant literature provides a synthesized overview of the current state of knowledge, develops a *meta*-framework to reconcile past research, identifies inconsistencies in prior results, and suggests areas for future research. To address these future directions, this study empirically extends the proposed *meta*-framework by testing impactful new variables. Structural equation modelling of survey data from 992 respondents in Hungary shows that drivers of behavioural intention to use AVs significantly differ among users with high and with low personal information technology innovativeness. The behavioural intention of innovative users is influenced by utilitarian and hedonic motivations, whereas laggards are driven by hedonic motivation, and a utilitarian motivation does not play a role. Innovative users' behavioural intention to use AVs is affected by specific technological fears (i.e., data privacy concerns), whereas those lagging are not influenced by specific, only by general concerns (i.e., overall technological anxiety). The study also shows how individual-level behavioural intention to use AVs interacts with expected societal-level outcomes (e.g., equal opportunity for mobility). The results shed light on the need for more research on the role of moderating variables, which are relatively unexplored in the extant literature yet can contribute to a better understanding of the differences in patterns between various groups of future users, offering important managerial implications.

1. Introduction

Autonomous vehicles (AVs) – conceptualized as Level 4 and Level 5 vehicles in this study (SAE, 2018) – are expected to revolutionize mobility systems in the coming decades. Automotive and tech companies alike are investing heavily in AV technologies, which are evolving in various modes; however, few vehicles have been deployed in test mode, and AVs are not yet available to the public. Former predictions about the adoption of AV technology have been overly optimistic. For example, one 2015 prediction forecasted that AVs would be piloting humans around US cities in significant numbers as soon as 2018 (Forbes, 2020), and General Motors claimed in 2018 that it would launch a fleet of cars without steering wheels or pedals in 2019 (Economist, 2019). These inaccurate forecasts signal that business think-thanks, tech firms, and car manufacturers do not have a precise plan for the public launch of AV technology.

Firms often overestimate user responses to innovations due to poor understanding of customer needs and variables that influence innovation adoption. According to prior studies, 50 to 75 percent of new innovations fail; only one-third of the new products that are

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introduced to the public become successful, and these failure rates have not decreased significantly over the last decades (Dijksterhuis, 2016; Ortt and Smits, 2006). Because AV is a radical innovation that carries more risks than incremental innovation, companies, and policymakers need to obtain a comprehensive view of the variables expected to influence the forthcoming adoption of AVs.

This research addresses the core element of the technology adoption process, behavioural intention to use (BIU) AVs (c.f., Davis et al., 1989), and formulates two research questions. First, what are the antecedents and consequences of behavioural intention to use AVs? To answer this question, we systematically review the extant body of literature and create an empirically derived taxonomy, the AV Acceptance Meta-framework (AVAM framework). Second, how can our current state of knowledge on the adoption of AVs presented in the AVAM framework be empirically extended? By answering this question, we propose and empirically test impactful new variables that influence the BIU.

The remainder of this paper is organized as follows. The following section presents the systematic review of the extant literature, followed by the AVAM framework and its empirical extension in section three. Next, the empirical study's research methods and key findings are described. The article concludes with a discussion of the study's theoretical contributions, managerial implications, limitations, and suggestions for future research.

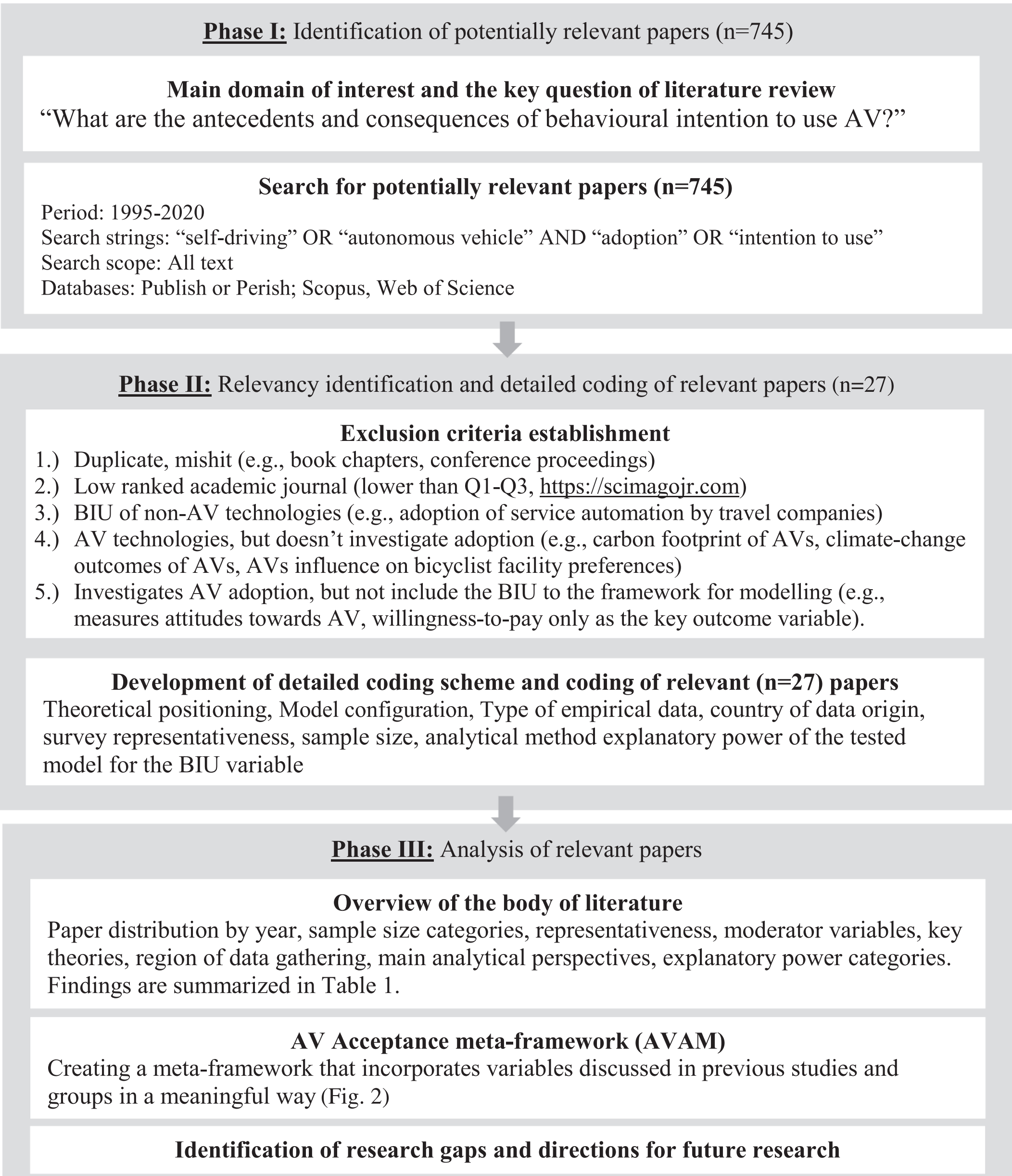


Fig. 1. Systematic literature review procedure and process.

2. A systematic review of AV acceptance studies

2.1. Procedure and process

To provide a solid background for this study, we conducted a systematic review of empirical studies on the acceptance of AVs, specifically on the antecedents and outcomes of behavioural intention to use AV, following the well-established guidelines by Tranfield et al. (2003).

As Fig. 1 shows, in Phase I of our systematic literature review, we identified potentially relevant papers. To answer the key question of our literature review - "What are the antecedents and consequences of behavioural intention to use AV?" - we conducted research for the strings "self-driving" OR "autonomous vehicle" AND "adoption" OR "intention to use" among journal publications between 1995 and 2020 in Harzing's Publish or Perish, Scopus, and Web of Science. Our search strategy included studies that contain a combination of these keywords in all text. These searches resulted in a total number of 745 potentially relevant studies.

As Fig. 1. depicts, in Phase II, to identify the relevant papers from potentially relevant ones, detailed criteria for exclusion were established. We first eliminated duplicates, mishits (e.g., book chapters, conference proceedings, lower-ranked journal articles), and non-empirical papers (e.g., review papers, editorials). To ensure the representativeness and high quality of studies included in our review, we examined influential journals ranked as Q1-Q3, according to the Scimago Journal Rank (https://www.scimagojr.com/) and removed papers from lower-ranked academic journals. Then, we excluded papers that focused on behavioural intention to use for non-AV-technologies or that examined AV technologies but did not consider their acceptance (e.g., carbon footprints of AVs). Finally, we did not include AV adoption studies that did not investigate the BIU in their AV acceptance study (e.g., measured only attitudes towards AV or willingness-to-pay as the key outcome variable).

For the sake of methodological rigor (Tranfield et al., 2003), we developed a detailed coding protocol using a scheme by which we coded every relevant paper (n = 27). In the coding scheme, we recorded the theoretical positioning, the model configuration (antecedents, moderators, mediators, and performance effects related to variable BIU), the methodological approach (the type of empirical data, country of data origin, survey representativeness, sample size, analytical method), and results (e.g., the explanatory power of the tested model for the BIU variable).

This coding scheme was the data repository from which subsequent analysis emerged in Phase III of our systematic literature review. We analysed relevant papers by providing an overview of the body of literature, creating an AV acceptance *meta*-framework of antecedents, moderators, and performance effects of BIU; and identifying research gaps in this body of literature.

Table 1
Description of body of literature on behavioural intention to use AV (n = 27).

Characteristics	Number of studies	Characteristics	Number of studies
Distribution by year [a]		*Theoretical underpinning*[b]	
2014–15	2	TAM (CTAM)	17
2016–17	5	UTAUT (UTAUT 2)	8
2018-	20	TPB	5
		No specific theory[c]	8
Sample size (average = 890)		*Region of data gathering*	
50–400	8	Asia	6
401–600	9	Europe	9
601–1500	6	North America	10
1501–3200	4	Not reported	2
Representativeness of sampling		*Analytical approach*	
Representative	4	SEM	12
Non-representative or not reported	23	Regression	13
		Other (e.g.: correlations)	2
Moderator variable[d]		*Explanatory value*[g] *(average = 0.46)*	
No moderator	22	0.0–0.3	4
No significant moderator[e]	3	0.31–0.5	4
Significant moderator[f]	2	0.51–0.7	10
		0.7–1.0	1
		Not reported	8

[a] Data gathering for the systematic literature review ended in January 2020.
[b] Three most frequently cited theories, number of articles in the categories does not equal with the total number of articles in the analysis (N = 27) as one study may have included several theories and empirical bodies of literature.
[c] The study does not anchor its theoretical framework, hypotheses/research questions, or discussion in a particular theory, nor cites or mentions a prior theory, builds upon empirical bodies of literature.
[d] Number of studies that empirically test variables moderating the link between any antecedents or consequences of BIU.
[e] Non-significant moderator variables investigated were the following ones: age, gender, experience, level of education, household income.
[f] Significant moderator variable: age.
[g] Explanatory value (R^2) related to the variable 'intention to use AV'.

2.2. Overview of the body of literature

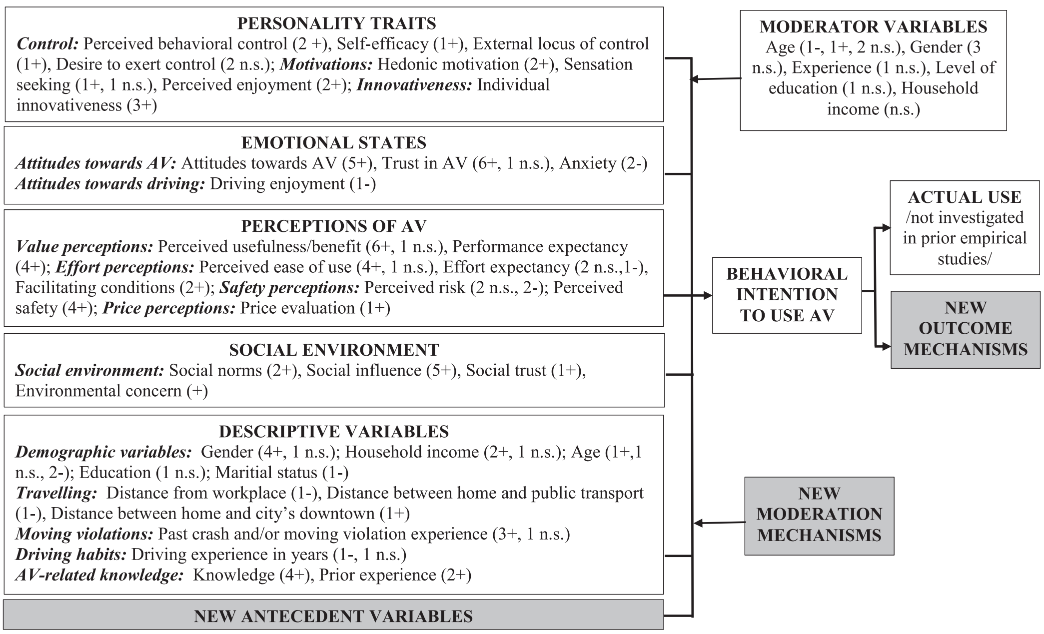
Table 1 summarizes the key characteristics of the body of empirical papers investigating BIU. The results on the annual distribution of relevant papers indicate a skyrocketing recent research interest in the topic of BIU; only 7 out of the 27 relevant papers were published prior to 2018, whereas the remaining studies are more recent. The most frequently used underlying theory is Technology Acceptance Model (TAM) and/or its variations, followed by the Unified Theory of Acceptance and Use of Technology (UTAUT). However, it is important to note that eight studies (30 percent) did not theoretically anchor or discuss the research in light of any particular theory, nor cite or mention a prior theory, but rather purely built upon empirical bodies of literature.

Regarding the methodological approaches, a majority of studies rely on sample size between 401 and 600 respondents, and four studies of the 27 use sampling techniques that are from some perspective (i.e., gender, income, age, education) representative for the whole population (Hohenberger et al., 2016; Kapser and Abdelrahman, 2020; Lee et al., 2019; Zmud et al., 2016), whereas the rest of the studies apply non-representative or convenience sampling approach (e.g., student sample). Most of the studies were conducted in economically developed western countries, with the United States being the most frequent place of data gathering (8 studies), followed by Germany (5 studies). Among European countries, France, Spain, and Greece also served as contexts for data gathering. The most frequent analytical techniques include structural equation modelling (e.g., Liu et al., 2019a; Montoro et al., 2019) and regression analysis (e.g., Hohenberger et al., 2016; Nodjomian and Kockelman, 2019).

We also analysed whether prior studies took moderator variables into consideration. Moderator variables explain the differential effects of the independent variable on the dependent variable by providing insight into the conditions under which this effect might vary depending on the moderator variable's value. Scholars have recently started to explore the role of these variables in the context of AV adoption, and yet only five studies consider moderator variables on the link between BIU and factors affecting it (Chen, 2019; Herrenkind et al., 2019b; Hohenberger et al., 2016; Koul and Eydgahi, 2018; Madigan et al., 2017). Of these studies, only two confirm the presence of the same significant moderator, age. Hohenberger et al. (2016) show that age negatively moderates the effect of biological sex on willingness to use through anxiety, whereas Herrenkind et al. (2019b) find that age positively moderates the effect of perceived usefulness and price evaluation on BIU. Finally, explanatory value for the antecedents involved in explaining BIU ranges between 0.01 and 0.76, with an average of 0.46. Appendix 1 lists the relevant studies for the systematic review.

2.3. The AV acceptance meta-framework (AVAM framework)

We depict the findings of the systematic literature review in a *meta*-framework format. Meta-frameworks are visual syntheses of previous empirical studies in one aggregated figure to provide an overview of the variables investigated previously. In addition to their academic value, *meta*-frameworks are considered to be relevant from a managerial perspective. Because most of the studies in our review tested conceptual links or hypotheses between variables, we follow this logic and distinguish between the antecedents



In parentheses those number of studies that confirmed positive (+), non-significant (n.s.) or negative (-) relationship between the specific variable and BIU. For example, Effort expectancy (2 n.s.,1-) indicating that 2 studies confirmed non-significant, one study negative link between this variable and BIU. Some variables (e.g., Gender, Household income, Age, etc.) are listed among both the antecedent and moderator variables, because some studies identified them as antecedents while other ones as moderators.

Fig. 2. The AV Acceptance Meta-framework (AVAM) and directions for extension.

(variables that logically precede and influence another variable, placed at the left side of the *meta*-framework) and performance consequences (placed at the right side of the *meta*-framework) of the BIU. We also provide an overview of variables investigated as moderators in previous studies.

The five main categories of the antecedents (i.e., personality traits, emotional states, perceptions, social environment, and descriptive variables) emerged as a result of an iterative grouping of variables investigated in prior studies. This iterative grouping approach is frequently used for *meta*-framework creation (e.g., Arli et al., 2018). The approach seeks to provide main categories for those groups of variables that are conceptually similar and hence can be assigned to the same group. This approach is iterative by nature, as these categories are not pre-defined and emerge as a result of the analysis. The approach aims to create meaningful main categories as building blocks for a *meta*-framework that conceptually covers the variables investigated in prior studies.

As the resulting *meta*-framework (Fig. 2) shows, the BIU is influenced by variables related to personality traits, emotional states related to both driving and AV, perceptions of AV, social environment, and variables that describe the individual (e.g., demographics, travelling habits, and moving violations).

Among the personality traits, variables related to control play important roles. Self-efficacy and perceived behavioural control reflect that the individual is confident in their ability to control AV and to solve unforeseen issues while using AV. Each of the studies reinforces that these variables positively influence the BIU(Chen and Yan, 2019; Lee et al., 2019; Moták et al., 2017). These results, showing that individuals with the impression of having control over their environment tend to show higher BIU, to some extent, contradicts the findings by Choi and Ji (2015). They find that external locus of control (i.e., the belief that one's behaviour will not lead to valued reinforcement, hence not under one's control) positively influences BIU. Scholars agree that the desire to exert control–which is conceptually different from the perceived level or external locus of control–has no significant impact on the BIU (Herrenkind et al., 2019a; Zmud et al., 2016). Motivations linked to hedonism (Kapser and Abdelrahman, 2020; Madigan et al., 2017) and perceived enjoyment (Herrenkind et al., 2019a) positively influence the BIU. However, the impact of sensation seeking is somewhat controversial. Whereas Payre et al. (2014) found a positive, Choi and Ji (2015) could not confirm a significant effect. The role of individual innovativeness in BIU has been shown in three different studies (Chen and Yan, 2019; Hegner et al., 2019; Sener et al., 2019).

The second group of antecedents is related to emotional states towards AV or driving. An overwhelming number of studies have confirmed that positive attitudes (Buckley et al., 2018; Chen and Yan, 2019; Herrenkind et al., 2019a; Moták et al., 2017; Payre et al., 2014) and trust in AV (Buckley et al., 2018; Hegner et al., 2019; Herrenkind et al., 2019a; Herrenkind et al., 2019b; Liu et al., 2019a; Panagiotopoulos and Dimitrakopoulos, 2018) enhance BIU. Anxiety (Hohenberger et al., 2016; Zmud et al., 2016), however, as well as positive attitudes towards driving (Hegner et al., 2019), reduce BIU.

Perceptions of AV, specifically value, effort, safety, and price perceptions, are also identified as critical drivers of the BIU. Perceived usefulness (e.g., Buckley et al., 2018; Hegner et al., 2019; Koul and Eydgahi, 2018) and performance expectancy (e.g., Madigan et al., 2017; Sener et al., 2019; Zmud et al., 2016) positively influence the BIU. Yet, the role of effort expectancy is less unequivocal: some scholars found no significant driving influence (Kapser and Abdelrahman, 2020; Madigan et al., 2017), whereas Sener et al. (2019) point out that less expected effort leads to higher BIU. In a similar vein, studies investigating the role of perceived risk also culminate into controversial results, with some studies finding no significant (Choi and Ji, 2015; Lee et al., 2019), whereas others confirm negative impacts (Kapser and Abdelrahman, 2020; Liu et al., 2019b). Perceived safety has a clear positive effect on the BIU (e.g., Montoro et al., 2019; Zmud et al., 2016).

Variables related to the social environment (e.g., social norm, social influence), the degree to which the individual has confidence

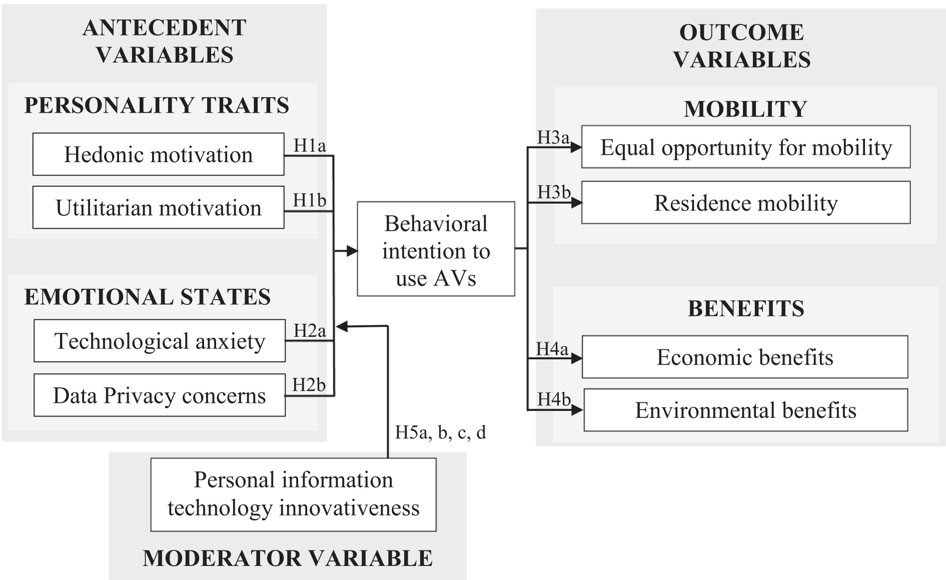


Fig. 3. Model of the empirical study.

in the society (e.g., Kapser and Abdelrahman, 2020; Liu et al., 2019b; Zmud et al., 2016), and environmental concerns (Wu et al., 2019) positively influence the BIU. The last group of antecedents is labeled as descriptive ones, including demographic variables (e.g., gender, income, age, education, and marital status). Prior studies show that men seem to be more receptive towards AVs (e.g., Bansal et al., 2016; Zoellick et al., 2019), whereas, for example, the role of age is less unequivocal (Bansal et al., 2016; Moták et al., 2017). Extant studies agree upon the positive influencing effect of the perceived level of AV-related knowledge and prior experience with the technology (e.g., Robertson et al., 2019), and several studies confirmed that prior crash and moving violations enhance the BIU (e.g., Bansal and Kockelman, 2018).

3. Empirical extension of the AVAM framework and hypotheses development

The AVAM framework (Fig. 2) presents a structured overview of the different variables that have been investigated in 27 various studies with the aim of synthesizing the extant body of literature, uncovering ambiguities, and depicting directions for future research. Hence, the *meta*-framework serves different purposes than the research model, which is the visual representation of the variables and the linkages among the variables to be empirically tested. For the sake of methodological rigour (e.g., unbiased effect estimates, the validity of confidence interval estimation), testing the whole AVAM within one empirical study is not suggested. As Heinze et al. (2018) state, “we are confronted with the number of candidate variables in the range 10–30. This number is often too large to be considered in a statistical model”.

The AVAM framework identifies three important directions for future research: (1) the involvement of new antecedent variables that have not been investigated previously but may serve as a critical influencer in the BIU, (2) the identification of new moderator variables that may distinguish acceptance patterns between group of users, and (3) additions related to new outcome mechanisms. In our empirical research, we aim to extend our current knowledge in each aspect, and we propose and test the research model depicted in Fig. 3.

3.1. Antecedent variables

Among the antecedent variables, we investigate hedonic and utilitarian motivations. This choice is justified by the fact that, although research on personality traits at BIU has received considerable attention, hedonic motivation specifically is found to be a predictor of key importance (Madigan et al., 2017), whereas less is known about the roles of other types of motivations. Although many motivations exist, most typologies consider hedonic and utilitarian motivations as fundamental to understand consumer behaviours (Childers et al., 2001). This notion is also echoed in the seminal work of Holbrook and Hirschman (1982), who claim that consumers follow different behavioural patterns when making decisions and can be characterized as either “problem solvers” or those who seek “fun, fantasy, arousal, sensory stimulation, and enjoyment”. Despite its importance, utilitarian motivation and its interplay with hedonic motivation are understudied in the AV adoption literature and require further academic merit.

Motivation refers to an internal state that forces an individual toward the satisfaction of his or her basic needs and drives the individual’s willingness to act (Ryan and Deci, 2000). Hedonic motivation refers to behaviours in search of enjoyment and sensation seeking. Hence the benefit of hedonic motivation is experiential and emotional (Babin et al., 1994), whereas utilitarian motivation is defined as rational, decision effective, and goal-oriented (Hirschman and Holbrook, 1982). Hedonic customers seek novel, varied, and complex sensational experiences and willing to take risks; thus, they are more likely to accept the novelty and risks associated with self-driving cars (Osswald et al., 2012).

Utilitarian motivation is related to rationality, decision effectiveness, and goal orientation that forces an individual towards the satisfaction of his or her basic needs and drives an individual’s willingness to act (Ryan and Deci, 2000). As utilitarian benefits (e.g., performance expectancy, perceived usefulness) are important aspects when accepting AVs, we claim that although some users may be driven by hedonic motivations, sensation seeking, and perceived enjoyment (e.g., Herrenkind et al., 2019a; Kapser and Abdelrahman, 2020), others may be influenced by utilitarian motivations.

H1a:. Hedonic motivation has a positive effect on BIU.

H1b:. Utilitarian motivation has a positive effect on BIU.

The other pair of antecedents our research model investigates are technological anxiety and data privacy concerns. Although anxiety has been confirmed in two different studies to reduce the BIU, Hohenberger et al. (2016) as well as Zmud et al. (2016), used a single item (one question only: “How frightening would such a car for you?” / “Self-driving vehicles are somewhat frightening to me.”, respectively) to capture this complex phenomenon. Hence, more research and the use of referred scales tested for reliability and validity are needed to justify the link between anxiety and the BIU. Second, anxiety is an emotional state that includes feelings of tension, nervousness, apprehension, and worry, often accompanied by physiological arousal (Spielberger, 2010). Scholars emphasize the distinction between anxiety as an emotional state and the individual in anxiety as a personality trait (Spielberger, 2010), and yet this difference has not been captured in the extant body of literature. Our empirical study focuses on the previous one and considers technological anxiety. Technological anxiety is the tendency of individuals to be uneasy, apprehensive, or fearful about using innovative technological products such as AV (Sääksjärvi and Samiee, 2011). Because innovative products with a lack of usage experience have been found to increase uncertainty (Hoeffler, 2003), we propose that anxiety reduces BIU.

We chose to select data privacy concerns as an antecedent in our research model because consumer-level data security is an increasingly important theme worldwide. For example, a recent survey showed that 93 percent of the respondents had some sort of data privacy concerns, with the most severe concerns being identity theft and fraud (72 percent) (Clement, 2019). Despite data security being firmly placed at the top of managerial agendas, the extant literature provides little guidance on how data privacy concerns shape BIU.

Data privacy concerns refer to a person's vulnerability due to loss of control over the management of individually identifiable personal information by other parties, such as firms or organizations (Martin et al., 2017). Individuals would only intend to use AVs when related; interconnected technology provides a sufficient level of data privacy and security protection (Panagiotopoulos and Dimitrakopoulos, 2018). The most severe concern related to AV stems from potential safety issues caused by the fear of attacks by hackers (König and Neumayr, 2017). By contrast, Gurumurthy and Kockelman (2020) claim that data privacy is not on the top of respondents' minds when general AV-related concerns are requested. It has long been suggested that data privacy issues can lead to changes in peoples' behaviours, for example, in the context of online shopping (Hille et al., 2015). We propose that data privacy concerns reduce the BIU; due to fears related to data privacy, consumers experience an adverse emotional reaction towards new technologies that evokes fear and confusion (Venkatesh, 2000), leading to reduced BIU.

H2a:. Technological anxiety has a negative effect on BIU.

H2b:. Data privacy concern has a negative effect on BIU.

3.2. Outcome variables

The theoretical models (i.e., TAM, UTAUT) on which the majority of empirical research on AV is based examine actual system usage as the ultimate outcome of the BIU. Because AV technology is not yet widely available, hence actual usage cannot be tested, the empirical research reviewed in this study looks only at the BIU as the outcome variable and does not examine its further outcomes (see Fig. 2). As the spread of AV will have significant social and economic impacts, we aim to extend the AVAM by considering the expected societal-level outcomes of the BIU.

Specifically, we investigate two mobility outcomes (equal opportunities for mobility (EOM) and residence mobility). Children or people with disabilities interact with various modes of transport in different ways, and the advent of AVs will impact these interactions. For example, people with severe visual impairments cannot drive; they are compelled to rely on taxis or lifts from family, but AVs will be able to navigate themselves to the required destination and independently find parking spaces after dropping off passengers (Bennett et al., 2019). As part of shifts in the future mobility system, AVs will have the most positive impact on exurban areas, which are connected to urban regions via limited access highways. Meyer et al. (2017) point out that "well-connected rural municipalities experience the strongest increase in accessibility, while the effect in city centers is much less strong or even negative." These results indicate that users may, as a result of the wide-spread use of AV, become more interested in relocating farther from central urban areas.

H3a:. BIU has a positive effect on EOM.

H3b:. BIU has a positive effect on residence mobility.

The second group of outcome variables is related to the economic and environmental benefits of AVs. Recently, scholars have started to pay more attention to the shared AV technology, recognizing its potential benefits to society. The proliferation of AVs will also transform car ownership models. AV users may intend to relinquish their household vehicles and instead call an AV on demand when their traffic needs arise. Moreover, new travel mode choices resulting from AV do not expect to culminate only in reduced car ownership but also in reduced associated negative impacts on the environment. A review by Hao and Yamamoto (2018) highlights that AVs are likely to accrue environmental benefits, such as a reduction in greenhouse gas emissions.

H4a:. BIU has a positive effect on economic benefit.

H4b:. BIU has a positive effect on environmental benefit.

3.3. Moderator variable

As shown in Table 1, only a limited number of studies consider moderator variables among those that focus on the BIU. These variables are descriptive, including age, gender, education, and household. Among these variables, only age was found to negatively moderate the effect of biological sex on BIU (Hohenberger et al., 2016). Madigan et al. (2017) conclude that age, gender, income, and experience may not be relevant in the context of automated transport as a moderator variable. This evidence is in sharp contrast with previous studies such as that by Venkatesh et al. (2012), founders of the UTAUT model, who found evidence for the effects of all of the aforementioned moderators.

Leicht et al. (2018) draw attention to the moderator role of consumer innovativeness–conceptualized as consumer's general willingness to try new things– in the AV context, which reinforces the causal relationship between variables influencing AV adoption and purchase intention. It has long been suggested that some individuals are more willing to take a risk by trying out an innovation, whereas others are hesitant to change their practices (cf. Rogers, 1983). AVs represent radical innovation as a destructive technology that challenges current best practices in worldwide mobility. Accordingly, the seminal work of Agarwal and Prasad (1998) suggests extending dominant technology acceptance models with the inclusion of personal innovativeness by explicating the role of individual traits in technology adoption.

Accordingly, this study includes personal information technology innovativeness (PITI) as a moderator variable both between BIU and its investigated antecedents and consequences. PITI is defined as the "willingness of an individual to try out any new information technology" (Agarwal and Prasad, 1998). PITI is conceptualized as a personality trait and hence considered a stable descriptor of individuals who is invariant across situational considerations, and as such, not idiosyncratic to a specific configuration of situational factors (Agarwal and Prasad, 1998).

Research shows that IT systems can be used both for fun (i.e., hedonic motivation) and productivity (i.e., utilitarian motivation), and fun can be as or even more important than productivity for many users. When users start to adopt a particular new technology, they tend to pay more attention to the joy derived from its novelty and may even use it for the sake of novelty (Holbrook and Hirschman, 1982). However, users with high PITI are more accustomed to using novel technologies. The perceived novelty associated with AV adoption that drives the impact of hedonic motivation on BIU will diminish, and users are expected to start adopting AVs for more pragmatic, utilitarian purposes such as gains in efficiency or effectiveness (Venkatesh et al., 2012).

H5a:. High PITI weakens the positive effect of hedonic motivation on BIU.

H5b:. High PITI strengthens the positive effect of utilitarian motivation on BIU.

High technology novel products are associated with a high level of uncertainty and complexity, leading to user anxiety. We expect that users with high PITI experience lower levels of anxiety when embracing new technology due to their experience and self-efficacy in interacting with technologically complex innovations (Herrenkind et al., 2019a). However, we expect high PITI users to be more anxious about data theft attempts than their peers who are less technologically innovative. We assume that high PITI users are likely to have more knowledge of data theft attempts, thus overestimating its importance as a driver of BIU.

H5c:. High PITI weakens the negative effect of technological anxiety on BIU.

H5d:. High PITI strengthens the negative effect of data privacy concerns on BIU.

4. Participants and procedures of the empirical study

Data for this study were collected using an online questionnaire with a convenience sampling approach using the Qualtrics survey tool platform. We administered the questionnaire to the Facebook group of a major automotive savvy online community in Hungary, 'Totalcar' (www.totalcar.hu), which has about 150.000 fans and followers. To reach a more general population, we also gathered data from master students at a major Hungarian University.

The questionnaire commenced with a description of the study's purpose and an explanation of fully automated vehicles and their functions (equivalent to the highest level of automation of the SAE standard). The questionnaire included measures for the ten key constructs: behavioural intention to use AVs, personal information technology innovativeness, hedonic motivation, utilitarian motivation, technological anxiety, data privacy concerns, equal opportunity for mobility, residence mobility, economic benefits, and environmental benefits. Each construct was measured with multiple items; the majority of the scales were adopted from or inspired by existing studies, using five-point Likert-scales with anchors for all items (see Appendix 2). The questionnaire was administered in Hungarian, and hence the scale items that were adopted from prior studies were translated from English by two independent translators applying the backward translation approach (Brislin, 1970). Following the translation procedure, the researcher made comparisons of the initial and the back-translated questionnaires, checking for content changes and mistranslations. This test resulted in minor word-changes in the Hungarian language questionnaire.

Prior to large-scale data gathering, the study questionnaire was further tested using a three-stage process. First, an academic with notable experience in survey research evaluated the questionnaire according to its fit with Hungarian market research practice and was asked to identify items that may cause confusion or would be expected to overtax respondents' patience. Second, we involved an expert with a decade of experience in the automotive industry who performed a semantic review of the questionnaire. He checked for the face validity of the AV-related scale items (e.g., equal opportunity for mobility, residence mobility, data privacy concerns) from an automotive industry-specific view. Third, 12 students pre-tested the questionnaire. We asked them to fill out the questionnaire and list items that they found confusing, incoherent, or hard to respond to. They were asked to briefly describe their problems with each item and to measure how much time it took them to complete the questionnaire. Based on these pre-tests, we made minor modifications in the questionnaires (e.g., eliminated items in denial mode, because the Hungarian respondents had difficulties interpreting the low scale value for these scales items).

5. Results

5.1. Data screening

We followed the guidelines of Armstrong and Overton (1977) to detect biases due to non-response, which suggest comparing responses (i.e., variables included in the model and key descriptive characteristics of respondents) submitted by quick versus slow respondents to detect significant changes. This analysis did not indicate significant differences. Common method bias (c.f. Podsakoff et al., 2003) was assessed using Harman's single factor method (Harman, 1976). All remaining measure items included in the final measurement model were entered into an exploratory factor analysis. The unrotated factor solution shows that no single factor explains the majority of the variance, suggesting that common method bias is not a major concern in this study.

Table 2
Results of discriminant validity of measures and correlation matrix.

Constructs	ME	SD	CA	CR	AVE	1	2	3	4	5	6	7	8	9	10
1. BIU	3.09	1.22	0.88	0.89	0.74	0.86									
2. PITI	2.85	1.06	0.87	0.87	0.64	0.24	0.79								
3. Hedonic motivation	2.13	1.25	0.91	0.92	0.74	0.75	0.10	0.86							
4. Utilitarian motivation	3.15	1.11	0.88	0.89	0.67	0.48	0.10	0.47	0.81						
5. Technological anxiety	2.54	1.25	0.87	0.87	0.62	−0.53	−0.29	−0.34	−0.21	0.79					
6. Data privacy concerns	3.23	1.26	0.76	0.77	0.52	−0.33	−0.12	−0.27	−0.18	0.55	0.72				
7. EOM	4.06	0.92	0.86	0.86	0.75	0.27	0.18	0.23	0.22	−0.34	−0.16	0.86			
8. Residence mobility	2.93	1.14	0.89	0.89	0.74	0.41	0.10	0.41	0.31	−0.25	−0.17	0.34	0.86		
9. Economic benefits	3.06	1.17	0.78	0.79	0.56	0.53	0.21	0.38	0.26	−0.55	−0.33	0.44	0.55	0.74	
10. Environmental benefits	3.76	1.08	0.88	0.89	0.80	0.34	−0.03	0.36	0.27	−0.18	−0.21	0.16	0.26	0.37	0.89

BIU: behavioural intention to use AVs; PITI: personal information technology innovativeness; EOM: equal opportunity for mobility; ME: Mean; SD: Standard Deviation; CR: Composite Reliability; CA: Cronbach's Alpha; AVE: Average Variance Extracted. Value on the diagonal is the square root of AVE. Correlations in an absolute value under 0.10 are non-significant; between 0.10 and 0.12 are significant at the 0.01 and above 0.12 at the 0.001 level.

5.2. Demographic analysis

The two surveys yielded a total of 992 (664 and 328, respectively) usable responses. Respondents from the automotive savvy community were typically men (93.4%) in their early thirties (mean age: 31.4; min/max: 15/73, standard deviation: 8.7 years) with higher-level education (73.7 percent of respondents have been studying or graduated in universities); 83.3% lived either in the capital or in major cities or towns. Student respondents were typically female (70.4%); 93.6 percent of the respondents were between 21 and 26 years of age (mean age: 23.6; min/max: 21/47, standard deviation: 2.7 years); 78.7% had a residency in the capital or major cities.

5.3. Measurement model

All statistical analyses were performed using ©IBM SPSS (Statistical Package for Social Sciences), version 26.0, and ©IBM SPSS AMOS, version 26.0. We used confirmatory factor analysis (CFA) to test for the reliability and validity of measurement instruments. The results indicate a good fit, as all related metrics are acceptable compared to the cut-off values. The Chi-square /df ($\chi 2$/df) is less than 2.5; the comparative fit index (CFI) is greater than 0.90; the root mean square error of approximation (RMSEA) is not greater than 0.08, and the standardized root mean square residual (SRMR) is less than 0.08 (Byrne, 2010). As Appendix 2 shows, all of the standardized factor loadings are statistically significant ($p < .05$) and greater than 0.50 (Anderson and Gerbing, 1988). The fit indices for the measurement model are: $\chi 2 = 1215.13$, df = 416; $\chi 2/df = 2.92$; p = .000; CFI = 0.96, SRMR = 0.04, and RMSEA = 0.04. The results of the measurement instrument testing are summarized in Table 2.

Table 2 presents the means (ME) and standard deviations (SD) for the scales used for measurement related to the assessment of construct reliability. Cronbach's alpha (CA) and composite reliability (CR) measures are higher than the 0.70 threshold (Nunnally, 1967), indicating good reliability of the constructs, whereas the average variance extracted (AVE) is also greater than the cut-off value of 0.50 (Bagozzi and Yi, 1988). These tests confirm the convergent validity of the measures. As Table 2 shows, the correlation between two constructs is less than the square root of AVE, indicated on the diagonal, signalling discriminant validity (Fornell and Larker, 1981).

5.4. Structural model

We relied on the overall sample to test the direct hypotheses (H1-4).

The results (Table 3) indicate that hedonic and utilitarian motivations have significant, positive effects (b = 0.58 and 0.16, $p < .001$, respectively); technological anxiety has a significant negative effect (b = −0.33, $p < .001$), and data privacy concern has no significant effect on BIU (b = 0.02, n.s.). Hence H1a, H1b, and H2a are accepted, but H2b is rejected. These antecedent variables explain 69 percent of BIU's variance ($R^2 = 0.69$). Testing of the outcome variables shows that BIU has a significant positive effect on all investigated variables (EOM, residence mobility, economic, and environmental benefits), and explains 9, 20, 31, and 13 percent of its variance (R^2), respectively. Hence H3a, H3b, H4a, and H4b are accepted.

To test for the moderating effects of PITI, we performed a $\chi 2$ difference test. We created two subsamples of the whole dataset according to the respondents' PITI, by ranking them according to their mean value of the four items measuring PITI. In order to markedly reveal the differences between high and low PITI respondents, we compared the approximate top and bottom ten percent of users according to their PITI. High PITI respondents are those with an average score under or equal to 4.25 (N = 91 respondents), and

Table 3
Summary of structural relationships results.

Direct effects	Std. estimate	Hypothesis testing result
Antecedents of BIU[a,b]		
Hedonic motivation → BIU [b]	0.58***	H1a accepted
Utilitarian motivation → BIU [b]	0.16***	H1b accepted
Technological anxiety → BIU [b]	−0.33***	H2a accepted
Data privacy concern → BIU [b]	0.02	H2b rejected
Outcomes of BIU		
BIU → EOM[c,d]	0.31***	H3a accepted
BIU → Residence mobility[e]	0.44***	H3b accepted
BIU → Economic benefits[f]	0.56***	H4a accepted
BIU → Environmental benefits[g]	36***	H4b accepted

Model fit: $\chi 2$ (9 9 9) = 2477.83; $\chi 2$/df = 2.48; $p < .001$; RMSEA = 0.03; SRMR = 0.07; NNFI = 0.92; CFI = 0.93; *** $p < .001$.

[a] Behavioural intention to use AVs.
[b] R^2 (variance explained) = 0.69.
[c] Equal opportunity for mobility.
[d] R^2=.09.
[e] R^2=.20.
[f] R^2=.31.
[g] R^2=.13.

low PITI respondents are those with an average score below or equal to 1.5 (N = 86 respondents).

In testing whether the relationships between the four investigated antecedent variables and BIU differ across high and low PITI respondents (H5 a, b, c, d), we first compared a fully constrained model in which the paths are constrained to equal across subgroups (i. e., respondent with high and low PITI) to an unconstrained model in which the paths are allowed to vary freely. The results of the $\chi 2$ difference test showed that the two subgroups vary at the model level ($\Delta\chi 2(27) = 55.52$, $p < 0.001$), indicating that differences in the path relationships between high and low PITI respondents exist. In order to reveal which path estimates vary between the countries and which do not, we moved on to calculate the significant differences path by path.

The results presented in Table 4 indicate great differences across the high and low PITI respondent groups. Specifically, high PITI does not moderate the positive effect of hedonic motivation on BIU; hence H5a is rejected. However, high PITI positively moderates the positive effect of utilitarian motivation on BIU; hence H5b is accepted. High PITI weakens the negative effect of technological anxiety but strengthens the negative effect of data privacy concern on BIU; hence H5c and H5d are accepted.

6. Discussion

6.1. Responses to research questions and general discussion

Our study aims to enrich AV acceptance research and practice by providing an integrated, synthesized overview of the current state of knowledge on which antecedents influence BIU, as well as identifying inconsistencies, describing insights, outlining future research directions, and identifying existing gaps. As an attempt to address these gaps, using empirical data, this study seeks to elucidate how BIU is shaped and how it is estimated to impact the social environment by investigating impactful but thus far overlooked variables, and to unravel the role of contingencies.

More specifically, we aim to answer the following research questions.

(1) Based on the extant literature, what are the factors that directly influence BIU?
(2) How can this set of variables be empirically extended?

To provide a parsimonious conceptual foundation for studying AV adoption, based on a systematic review of the extant literature, we present an empirically derived taxonomy of variables that influence BIU, the AVAM framework. Our study contributes to a more fine-grained understanding of the antecedents of BIU by revealing that these can be categorized as personality traits, emotional states, perceptions of AV, variables related to the social environment, and descriptive variables (demographic ones, and travelling & moving habits). Systematic literature review reveals that previous research has focused on the antecedents of the BIU, and yet there are a number of inconsistencies on the impact of these variables, and expected outcomes are less understood. In addition, research moderators are seldom considered and largely confined to demographic variables.

Our empirical study proposes new antecedents, outcomes, and moderator variables to the investigation of the BIU. Our empirical results show that of the investigated antecedents, hedonic motivation has the strongest effect on the BIU in the overall sample, which is in accordance with previous findings. For example, Madigan et al. (2017) also find that hedonic motivation is the strongest predictor. According to our results, hedonic motivation is more than three times as impactful as utilitarian motivation in the merged sample. This is a new insight because utilitarian motivation as a direct antecedent has not yet been investigated. Although hedonic motivation is an equally important driver of BIU in high and low PITI groups, for technologically more innovative consumers, the importance of utilitarian motivation approaches hedonic motivation. By contrast, utilitarian motivation in the technologically laggard group has no significant effect on the BIU.

Technology anxiety has a negative impact on the BIU in the overall sample, which is in accordance with prior results on the impact of general anxiety (Hohenberger et al., 2016; Zmud et al., 2016). However, in the high PITI group, this effect is not significant, and hence among users who are usually the first to adopt IT innovations, technological anxiety is not likely to reduce the BIU. This effect is significantly negative in the IT-laggards group. Data privacy concerns in the overall sample have no significant effect on the BIU, whereas, in the high PITI sample, this is a significant deterrent. Hence, our results imply that the impact of the two investigated variables describing emotional states (anxiety and data privacy concerns) on the BIU is conditional on the technological innovativeness

Table 4
Results of multi-group moderation analysis.

Path	High PITI[a]		Low PITI		Model difference			Hypothesis testing
Direct effects	Std. estimate	p	Std. estimate	p	$\Delta\chi^2$	Δ df	p	
Hedonic motivation → BIU[b]	0.53	p < .001	0.56	p < .001	1078.28	1	ns[c]	H5a rejected
Utilitarian motivation → BIU	0.42	p < .001	0.13	ns	1087.12	1	p < .01	H5b accepted
Technological anxiety → BIU	0.05	ns	−0.37	p < .001	1083.56	1	p < .05	H5c accepted
Data privacy concern → BIU	−0.24	p < .05	0.05	ns	1083.41	1	p < .05	H5d accepted

[a] Personal information technology innovativeness.
[b] Behavioural intention to use AVs.
[c] non-significant. Critical value at 95 and 99 percent confidence for $\Delta\chi^2 = 1082.12$ and 1084.91, respectively ($\chi 2$ change greater than the critical value indicates a significant difference between the path estimates across the high and low PITO respondent groups).

of the prospective user. This differential effect may be explained by the users' prior knowledge. Presumably, high PITI users are more knowledgeable about technology-related topics, and hence the level of perceived technological anxiety is lower, but they have a deeper knowledge of the potential pitfalls of AV technologies, leading to over-estimation of the negative consequences of data-breach incidences. The BIU is expected to significantly reshape each of the examined social impacts (i.e., equal opportunity for mobility, residence mobility, economic, and environmental benefits).

In the empirical part of our research, we outlined a model that selects antecedents from personality traits and emotional states categories of the AVAM framework. Widely acknowledged technology adoption models such as TAM or UTAUT (e.g., Davis et al., 1989; Venkatesh et al., 2012) have contributed significantly to our understanding of the acceptance process of new technologies and have successfully been implied in the context of AVs (e.g., Wu et al., 2019). Nevertheless, these studies typically focus on influencing variables that belong to the perceptions of AVs (e.g., perceived usefulness and benefit, performance expectancy, perceived ease of use, effort expectancy). Variables of other AVAM categories receive less attention in studies that build on TAM and UTAUT. The explanatory power of our empirical research is 69 percent, which is higher than the average of previous research on the topic (46 percent) and implies that there is a reason d' être for researchers to explore new variables that go beyond traditionally used models.

6.2. Theoretical implications

The current research enriches AV adoption research by describing this emergent body of literature and addresses an important research gap by synthesizing the extant body of literature on the antecedents and outcomes of the BIU and moderators influencing these effects. Our study differs from prior literature reviews in the domain of AV adoption (e.g., Becker and Axhausen, 2017) because it has a distinct focus on the BIU as a core element of the adoption process; hence, it offers a more fine-tuned perspective of the variables that specifically influence this phenomenon.

Because the AVAM framework synthesizes more than three dozen variables tested in the 27 prior studies from the perspective of methodological rigor, it is not possible to test the AVAM framework at once (c.f., Heinze et al., 2018). Yet, it provides a state-of-the-art type of understanding of which variables influence the BIU of AVs and how these variables can be meaningfully grouped. These types of frameworks are typically considered to be highly relevant from a managerial perspective. As Dangelico and Vocalelli (2017) state, "We believe that it would be very useful to […] provide a framework to guide managers…". The AVAM framework also uncovers ambiguities and inconsistent results in the extant literature and outlines directions for future research.

This research opts to extend the current understanding of BIU adoption by uncovering the roles of an as-yet unelaborated antecedent, outcome, and moderator variables. Among the antecedent variables, the role of hedonic motivation has already been confirmed (e.g., Kapser and Abdelrahman, 2020), but the outcome difference of two motivations playing key roles in users' choices, hedonic and utilitarian, have not been considered in the context of AV adoption. This study sheds further light on the understanding of variables related to emotional states. Previous research has already confirmed the negative effects of AV-related anxiety on the BIU (Hohenberger et al., 2016), but less is known about how technological anxiety and data privacy, which have nowadays been firmly placed at the top of the managerial agenda, affect the adoption process. Although both technological anxiety and data privacy concerns describe an emotional state, the prior is general anxiety, without an objective identified underlying reason, whereas the latter is a specific fear of the occurrence of a well-defined event, a data breach. Our results reveal that from a conceptual point of view, it is essential to distinguish between general and specific anxiety and to recognize that users with deeper prior expertise, knowledge, and insights tend to be driven by their specific fears, but those with a lower level of understanding by their general fears.

Finally, this study contributes to an understanding of the expected societal-level outcomes of the BIU. Although both the TAM and the UTAUT models consider the actual use behaviour as the ultimate consequence of the BIU (Davis, 1989; Venkatesh et al., 2003), AV adoption involves not only individual but also social consequences; thus, it is important to predict the expected societal-level effects.

6.3. Managerial implications

Level 4 and 5 AVs are not yet available to the general public, but the taxonomy of the independent *meta*-model variables provides managers with an overview of which factors affect the BIU. Personality traits are relatively stable descriptors of individuals, and as such, cannot be directly influenced by decision-makers. At the same time, for example, these variables can provide a clue about the aspects of advertising that should be emphasized when technology becomes available. For example, hedonic motivation, sensation seeking, and enjoyment all suggest that it will be worth highlighting these types of motivations in communication by emphasizing how much fun it is to travel with such vehicles.

Unlike personality traits, emotional states can directly be influenced by AV decision-makers. Our results imply that attitudes towards AV significantly influence the BIU. Among these variables, trust and anxiety are impactful ones that greatly affect the BIU, so it is vital to improve trust and manage fears through communication. Managers need to emphasize that AVs are overall safe to use, and they should support these claims with illustrative data.

Our empirical research implies that lifestyle and personality-trait related variables outperform demographic variables when segmenting a group of variables, whose BIU is driven by different antecedents. Previous research has differentiated between respondent groups based on demographic variables; however, as the AVAM framework shows, these variables were insignificant moderators in the vast majority of the cases. Our research suggests that an individual's technological innovation may be a relevant segment forming criterion, and the BIU of high and low PITI receivers may be affected by different factors.

The results also highlight the need to reach out to leading users susceptible to technological innovation. For them, besides the hedonic motivations, the objective benefits that can be gained from using AV should also be emphasized. Communication towards this group of users should address not general but specific fears. By contrast, users who belong to the group of technological laggards should be addressed with emphasis on enjoyment value, and decision-makers should manage general anxieties rather than specific ones.

7. Limitations and directions for future research

As a result of this systematic literature research, several research gaps and fruitful areas for further research emerge. Despite the close scrutiny (we relied on three databases: Harzing's Publish or Perish, Scopus, and Web of Science), involving more databases may lead to finding further relevant studies. The resulting *meta*-framework shows, among the five groups of antecedent variables, the impact of factors related to perceptions of the AV is the most ambiguous. Specifically, out of the eight antecedent variables allocated to this group, four variables (perceived benefit, perceived ease of use, effort expectancy, and perceived risk) were found to have both significant and insignificant effects on the BIU in different studies. This result may be explained by the difficulty for respondents to evaluate and estimate the consequences of the perceptions of AV, a technology for which respondents lack empirical evidence. In fact, our empirical study also used respondents who have not yet traveled with AVs (but in our empirical research, we did not investigate AV-perception related variables). Hence, further research is needed to unravel extant ambiguities (e.g., the impact of perceived risk on the BIU) and to gain a more in-depth understanding of how perceptions of AVs shape the BIU. In order to make the perceptual variables more realistic for respondents, it may be worthwhile to combine a questionnaire that is considered mainstream in this body of literature with innovative methodological approaches, such as virtual reality, simulation, or gamification.

In our research, we used a convenience sample of respondents. Thus, for the sake of improving generalizability, it would be worthwhile to test the results on a representative sample. We took the AVAM framework as a starting point for our empirical research, but instead of focusing on resolving the ambiguities, we opted to identify new variables. Although our results show that PITI is an impactful moderating variable, future research may focus on defining additional variables that effectively differentiate between groups of users, where the BIU is affected by different variables. For example, millennials are a distinct target group in the automotive industry; it would be worth testing the effectiveness of group lifestyle and value attributes as moderating variables.

This study considered the individual's BIU, and – as extant survey type studies typically consider individual respondents – overlooks the BIU to use AVs by organizations. For example, less is known about how AVs will be implemented by organizations to improve the mobility of disabled passengers. Factors such as organizational resistance or the fear of current employees that their work may become unnecessary due to AVs may be examined. Finally, in this study, we have only glimpsed selected societal-level factors that may appear as outcomes of individual adoption of AVs. Further research is needed to understand the complex web of mechanisms between individual acceptance of AVs and its social impact.

8. Conclusions

The study provides a systematic literature review of the extant studies on the BIU. As part of this review, we describe the body of literature, systematize the antecedent variables into an empirically derived taxonomy, and create a managerially relevant *meta*-model that synthesizes prior research and outlines inconsistencies in the results. In order to empirically extend previous studies, we tested new antecedents, moderators, and outcome variables that were not investigated earlier but significantly affect the BIU. Our study's findings offer valuable insights for practitioners and researchers alike to increase the adoption of AVs.

Appendix 1:. List of studies relevant to the systematic literature review

Study	Theoretical positioning				Country of data origin	Res. Meth.		Surv. Repr.		N[9]	Anal. Tech.			R^2[2]
	A[1]	U[2]	P[3]	N[4]		S[5]	O[6]	R[7]	C[8]		S[10]	R[11]	O[12]	
Bansal et al. (2016)				√	US	√			√	347		√		0.06
Bansal and Kockelman (2018)				√	US	√			√	1088		√		0.04
Buckley et al. (2018)	√		√		US	√			√	74		√		0.49
Chen (2019)	√	√			Taiwan	√			√	700	√			0.52
Chen and Yan (2019)	√	√	√		Taiwan	√			√	574	√			0.60
Choi and Ji (2015)	√				n.r. [13]	√			√	552	√			0.67
Hegner et al. (2019)	√				Germany	√			√	369	√			0.64
Herrenkind et al. (2019a)	√				Germany	√	√[14]		√	268	√			n.r.
Herrenkind et al. (2019b)	√				US	√			√	1484	√			0.27
Hohenberger et al. (2016)				√	Germany	√		√[15]		1603		√		n.r.
Kapser and Abdelrahman (2020)		√			Germany	√		√[16]		501	√			0.76
Koul and Eydgahi (2018)	√				US	√			√	377		√		0.62
Lee et al. (2019)	√	√			Korea	√		√[17]		313	√			0.52
Liu et al. (2019a)	√				China	√			√	742	√			0.55
Liu et al. (2019b)				√	China	√			√	441				0.41
Madigan et al. (2017)		√			Greece	√			√	315		√		0.58
Montoro et al. (2019)				√	Spain	√			√	1205	√			n.r.
Moták et al. (2017)	√		√		France	√			√	532		√		0.54

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Study	Theoretical positioning				Country of data origin	Res. Meth.		Surv. Repr.		N[9]	Anal. Tech.			R^2
	A[1]	U[2]	P[3]	N[4]		S[5]	O[6]	R[7]	C[8]		S[10]	R[11]	O[12]	
Nodjomian and Kockelman (2019)				√	US	√			√	1422		√		0.01
Panagiotopoulos and Dimitrakopoulos (2018)	√	√			n.r.	√			√	483		√		0.43
Payre et al. (2014)	√				France	√	√		√	421		√		0.67
Robertson et al. (2019)	√		√		Canada	√	√		√	2662	√			n.r.
Sener and Zmud (2019)				√	US	√	√		√	3275			√	n.r.
Sener et al. (2019)	√	√	√		US	√			√	3097		√		n.r.
Wu et al. (2019)	√	√			China	√			√	470	√			n.r.
Zmud et al. (2016)	√				US	√	√	√[18]		556		√		n.r.
Zoellick et al. (2019)				√	Germany	√			√	125		√		0.49

[1] TAM and variations.
[2] UTAUT and variations.
[3] Theory of Planned Behaviour (TPB).
[4] The study does not anchor its theoretical framework, hypotheses/research questions, or discussion in a particular theory, nor cites or mentions a prior theory, builds upon empirical bodies of literature.
[5] Survey research method.
[6] Other research methods (stand-alone research method, e.g., we do not identify follow-up survey phone calls as stand-alone research).
[7] The gathered sample is representative for at least one variable.
[8] Convenience & non-representative sample.
[9] Sample size of data analysis for the BIU.
[10] Structural Equation Modelling.
[11] Regression Analysis.
[12] Other analytical techniques.
[13] Not reported.
[14] 15 depth interviews.
[15] Representative in terms of terms of biological sex, age, and education for Germany.
[16] Representative for age, gender, and monthly net-household income.
[17] Representative for gender of the Korean population, but not on age.
[18] The household income distribution for the sample was comparable with the population distribution for the Austin region, and education was slightly skewed toward higher educational attainment.

Appendix 2:. Measurement instrument of the empirical study in English and in Hungarian

Constructs and definition (measures inspired by or based on)	Items (factor loadings in parentheses)
Behavioural intention to use AVs: *the* strength of one's intention to perform a specified behaviour (i.e., use AV) (Davis et al., 1989; Wu et al., 2019) (reflective)	(5-point Likert scale, 1 = fully disagree, 5 = fully agree) ▪ Assuming AVs come into use, I will intent to try it (0.94) ▪ Assuming AVs come into use, I would like to use it on a regular basis (0.93) ▪ Assuming AVs come into use, I will switch to using AVs (0.66)
Personal information technology innovativeness: the willingness of an individual to try out any new information technology (Agarwal and Prasad, 1998) (reflective)	(5-point Likert scale, 1 = fully disagree, 5 = fully agree) ▪ If I heard about new information technology, I would look for ways to experiment with it (0.87) ▪ Among my peers, I am usually the first to try out new information technologies (0.73) ▪ In general, I am hesitant to try out new information technologies[1] (0.85) ▪ I like to experiment with new information technologies (0.69)
Hedonic motivation: the degree to which enjoyment and sensation-seeking force an individual towards the satisfaction of his or her basic needs and drive individuals' willingness to act. (Childers et al., 2001; Ryan and Deci, 2000) (reflective)	(5-point Likert scale, 1 = far below the competitors, 5 = far above the competitors) ▪ Travelling with AVs would be fun for its own sake (0.92) ▪ Travelling with AVs would make me feel good (0.92) ▪ I would spend time spared by using AVs for having fun (0.67) ▪ Travelling with AVs would be enjoyable (0.90)
Utilitarian motivation*:* the degree to which rationality, decision effectiveness, and goal orientation force an individual towards the satisfaction of his or her basic needs and drive individuals' willingness to act. (Ryan and Deci, 2000); new scale (reflective)	(5-point Likert scale, 1 = fully disagree, 5 = fully agree) ▪ While travelling with AV, I would spend my time working (0.71) ▪ While travelling with AV, I would spend my time organizing and communicating in work-related matters (0.84) ▪ While travelling with AV, I would spend my time to accomplish my work-related tasks (0.82)

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Constructs and definition (measures inspired by or based on)	Items (factor loadings in parentheses)
	▪ While travelling with AV, I would spend my time with administrative tasks (0.87)
Technological anxiety: the tendency of individuals to be uneasy, apprehensive, or fearful about using technological products (Osswald et al., 2012; Venkatesh and Davis, 2000) (reflective)	(5-point Likert scale, 1 = fully disagree, 5 = fully agree) ▪ I have concerns about using the system (0.87) ▪ I think I could have an accident because of using the system (0.85) ▪ The system is somewhat frightening to me (0.68) ▪ I am afraid that I do not understand the system (0.73)
Data privacy concerns: a person's vulnerability due to loss of control over the management of individually identifiable personal information by other parties, such as firms, organizations, etc. (Martin et al., 2017); new scale (reflective)	(5-point Likert scale, 1 = fully disagree, 5 = fully agree) ▪ I am afraid that the data (e.g., position, routes) collected about me during my travels will be stolen (0.77) ▪ I am afraid that the AV I am using will be attacked by hackers (0.74) ▪ I am afraid that data entry during my travel will be breached and the AV will miss-navigate (0.64)
Equal opportunity for mobility: the level of expectation that AVs will shape the mobility of children or people with disabilities; new scale (reflective)	(5-point Likert scale, 1 = fully disagree, 5 = fully agree) ▪ AVs will help people with disabilities to travel more easily and independently (0.90) ▪ AVs will make it easier for children to travel more easily independently (0.82)
Residence mobility: the level of expectation that as an outcome of AV proliferation, users will be interested in relocating farther from the central urban areas; new scale (reflective)	(5-point Likert scale, 1 = fully disagree, 5 = fully agree) ▪ With the proliferation of AVs, more people would commute daily between cities (0.83) ▪ The proliferation of AVs would help people move further from the center of big cities (0.89) ▪ The proliferation of AVs would make it easier to get from the smaller towns to the big cities (0.85)
Economic benefits: the degree of financial gains resulting from the proliferation of AVs; new scale (reflective)	(5-point Likert scale, 1 = fully disagree, 5 = fully agree) ▪ With the proliferation of AVs, fewer cars are needed per family (0.79) ▪ AVs would make travel more economical (e.g., always using the ideal route) (0.72) ▪ Insurance premiums would be lower with the proliferation of AVs (0.73)
Environmental benefits: the degree of environmental gains resulting from the proliferation of AVs, new scale (reflective)	(5-point Likert scale, 1 = fully disagree, 5 = fully agree) ▪ The proliferation of AVs would reduce the level of air pollution (0.91) ▪ AVs would be environmentally friendly compared to conventional cars (0.87)

Fit indices of confirmatory factor analysis: $\chi2(4\ 1\ 6)=1215.13$; $\chi2/df=2.92$; $p<.001$, CFI=.96; SRMR=.04; RMSEA=.04, All loadings are significant at the $p<.001$ level.

[1] Reverse scaled item.

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