ARTICLE IN PRESS

Technovation xxx (xxxx) xxx

Contents lists available at ScienceDirect

Technovation

journal homepage: www.elsevier.com/locate/technovation

"Baby, you can drive my car": Psychological antecedents that drive consumers' adoption of AI-powered autonomous vehicles

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ARTICLE INFO

Keywords:
Self-driving cars
Artificial intelligence
Technology acceptance model
User well-being
Social recognition
Hedonism
Privacy concerns
Technology trust

ABSTRACT

Artificial intelligence (AI)-powered autonomous vehicles (AVs) are one of the most highly anticipated technological advancements of our time, with potentially wide-ranging social implications in terms of driver/passenger safety, equity and environmental aspects. However, most consumers feel reluctant towards the adoption of AI-powered AVs. To analyse user acceptance of AI-powered AVs, we need to understand the related psychological, social and cognitive factors. To do so, we established a conceptual model based on the technology acceptance literature and considered how performance and effort expectancy, social recognition, hedonism technology security and privacy concerns influence both technology trust and user well-being as mediators that subsequently influence the behavioural intention of the use of AI-powered AVs. We used user innovativeness as a moderator, and we performed a survey in France. Our results from the structural equation modelling largely support the positive relationship between the behavioural intention to use AI-powered AVs and performance-/effort expectancy, social recognition, well-being, hedonism and technology trust, as well as security. On the other hand, privacy concerns negatively influence technology trust.

1. Introduction

In today's digitalized world, technologies such as artificial intelligence (AI), the Internet of Things (IoT), and smart connected objects are taking the lead (Novak and Hoffman, 2019). The increasing development of AI—generally defined as machines and systems that are able to perform tasks that normally require human intelligence—is rapidly changing the marketing landscape (Huang & Rust, 2020, 2021). Currently, we are assisting with the increasing infusion of technology into product and service settings, where humans are progressively supported, augmented, and sometimes substituted by machines (Ostrom et al., 2019).

In this regard, many innovations, including AI-based robots and AI-powered autonomous vehicles (AVs), are progressively enriching the marketing context (van Doorn et al., 2017; Huang and Rust, 2020; Huang and Rust, 2021). Autonomous vehicles (AVs) are capable of sensing their environment and operating without human involvement. A human passenger is not necessarily required to take control of the vehicle at any time, nor is a human passenger required to be present in the vehicle at all. AVs could help ease traffic congestion, lower pollution, and prevent accidents. AVs are vehicles in which human drivers are never required to take control to safely operate the vehicle. Additionally, AVs combine sensors and software to be able to control, navigate, and drive, which is why they are known as autonomous or "driverless" cars. AVs are intelligent vehicles that are equipped with communications network-linking sensors and devices that can be remotely monitored, accessed or controlled and that provide services that respond to the needs of their drivers (Koopman and Wagner, 2017). AVs are characterized by an interconnectedness of sensors, captors, the IoT, information and remote communication devices, such as smartphones and AI, which automates driving systems. These smart devices sense their surroundings and engage in real-time data collection, interaction, and feedback analysis. AVs not only execute tasks that are explicitly assigned by users but also actively collect big data from the environment and use AI to propose suitable solutions for drivers' comfort and security (Kapser and Abdelrahman, 2020). The AI service operates by self-understanding drivers' behaviours to optimize or automate decision making and well-being and achieve intelligent controllability (Sener et al., 2019). Automation means "the execution by an AI-based machine agent (usually a computer) of a function that was previously carried out by humans" (Parasuraman and Riley, 1997). AVs are one of the most highly anticipated technological advancements of our time, with potentially

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https://doi.org/10.1016/j.technovation.2021.102348
Received 16 October 2020; Received in revised form 21 April 2021; Accepted 10 July 2021

wide-ranging social implications in terms of driver/passenger safety, equity and environmental aspects (Holstein et al., 2018). First, many thousands of people die in motor vehicle crashes every year; thus, self-driving vehicles could hypothetically reduce that number due to AI. Second, self-driving technology could help mobilize individuals who are unable to drive, such as elderly or disabled people. Third, there are serious environmental advancement aspects, such as vehicles being electrified, and CO2 emissions dropping significantly. For all these reasons, AI-powered AVs have been widely seen as promising for enhancing the overall quality of life and well-being by providing personalized services and experiences (Xu et al., 2011). According to the European Road Transport Research Advisory Council (ERTRAC, 2017), AI-powered autonomous cars will be available on the EU market starting in 2030. The greatest and most appealing benefit of AVs is road safety, as 95% of accidents are caused by human error (European Parliament, 2019). Furthermore, due to the reduction of emissions, AVs can better protect the environment, create new jobs, expand economic growth, and increase mobility for the elderly population and those who are restricted in their mobility or are disabled. By 2023, the worldwide sale of autonomous vehicles that can drive without human supervision will reach 745,705 units (Gartner, 2018). According to a study by the think tank IDATE, AI-based autonomous vehicles represent a potential market of 55 million vehicles sold within 20 years (Ropert, 2019). Asian countries will be in first place in terms of AV sales by 2040. AVs are currently a reality. The technologies used for AVs are becoming increasingly accessible (lidar, sensor fusion, artificial intelligence, 5G), and regulations are becoming more flexible. Already, the first semi-autonomous vehicles have been marketed, and complete autonomous driverless vehicles, such as the Google Car or the French Navya, are appearing.

However, even if AI and AV technologies appear to be becoming increasingly present, many consumers are still reluctant to use these technologies (Statista 2018) because they do not want to delegate their decision-making authority either partially or fully to AI and machines. Their concerns include the loss of control, the loss of freedom, privacy issues, hacking, uncertainty, distrust, and fear that technology could harm their health and security. The literature shows three main barriers for potential users that negatively affect the intention to use AV as antecedents: privacy concerns; fear of technology, namely, vehicle and system security (from hackers); and the confusion of autonomous cars in unexpected situations (Statista 2020). Hence, there is currently no overall acceptance towards adopting AVs despite the potential performance, security, hedonistic and social benefits. Indeed, according to the "Automated Driving Roadmap" published in 2017 by the ERTRAC, "user security, privacy concerns and ethics, and societal and social acceptance" present challenges for the adoption of AV.

Nevertheless, few academic and empirical studies have been conducted to explain users' willingness or reluctance to drive AVs. Understanding how and why users accept or reject AI-based AVs is an important issue, according to numerous calls for research about AI and smart environments (Gao and Bai, 2014; Verhoef et al., 2017); therefore, it is important to understand consumer attitudes towards and perceptions of these new technologies (Mahmassani, 2016).

This study therefore contributes at both the theoretical and managerial levels, as most of the research in the domain of AI-based AVs comes from the engineering and computer science literature rather than the management literature. At a theoretical level, our study offers four main contributions to marketing and management research, which shed light on consumers' perceptions of AI-based AVs. Overall, our research aims to explore the both light and dark sides of AI-based AVs and contributes to the literature about technology acceptance theories (Davis, 1989) by developing an enhanced UTAUT (unified theory of acceptance and use of technology) model (Venkatesh et al., 2012) to understand the success factors and perceptions of AI-based AVs (Kulviwat et al., 2007; Ostrom et al., 2019). First, to contribute to the understanding of AV acceptance, we employ established UTAUT technology acceptance and usage benefit variables (Venkatesh et al., 2012), such as performance expectancy (the users' feelings of improved performance when using a new technology) and effort expectancy (how a person believes that using a particular technology would be free of effort or to its degree of ease). Second, we contribute by enhancing the UTAUT model with rarely investigated affective variables such as social recognition and hedonism. Our third and main contribution is that we introduce the impact of AI-based AVs on users' well-being, which is an emerging concept in consumer behaviour and marketing research, namely, transformative consumer research. As there is scant research that investigates customer resistance to technological innovations (Laukkanen, 2016; Talke and Heidenreich, 2014), a fourth contribution is our study of rarely investigated cognitive factors of technology resistance, namely, privacy concerns, technology security, and their impact on technology trust towards AVs (Gilly et al., 2012; Kleijnen et al., 2005; König and Neumayr, 2017). Finally, user innovativeness (Rogers, 1995) serves as a moderator.

Overall, our research aim is to understand the factors of AV adoption. We thus aim to answer the following research questions about AV perceptions and adoption:

1. What is the AV-related impact of social recognition and hedonism on user well-being?
2. What is the impact of privacy concerns and technology security on trust in AVs?
3. What is the impact of performance expectancy, user wellbeing and technology trust on the behavioural intention to use an AV?

To address the research gaps and by using an extent review of the literature and empirical data drawn from AV scenarios, this study seeks to contribute to a better understanding of the antecedents of the behavioural intention to use an AV, namely, perceptions of AV benefits, security and risk perceptions, variables related to the social environment, and emotional states, such as user well-being.

Our article is organized as follows. First, in the literature review, we provide an integrated, synthesized overview of the cognitive, affective and social antecedents that (in)directly influence the behavioural intention to use an AV. Then, we formulate our hypotheses, followed by a description of the methodology and data. We then present and discuss the results. Finally, we conclude by showing the managerial implications, addressing research limitations, and outlining possibilities for future research directions.

2. Conceptual framework and hypotheses development

In this section, we first define AI-powered autonomous vehicles (AVs), and then we perform a literature review to explain the concepts that we use in the UTAUT model, followed by our hypotheses.

2.1. AI-powered autonomous vehicles

The Society of Automotive Engineers (SAE, 2018) currently defines six levels of driving automation ranging from level 0 (fully manual) to level 5 (fully autonomous; steering wheel is optional, with no human intervention required at all). A fully automated AI-based AV takes over all functions and never needs to ask for human intervention. AVs are capable of sensing their environment and operating without human involvement. They can control their own steering, acceleration and deceleration, monitor their driving environment, and engage in a fallback setting in which the driver has his or her hands off the wheel and eyes off the street. A human passenger is not required to take control of the AV at any time, nor is a human passenger required to be present in the vehicle at all. AVs could help ease traffic congestion, lower pollution, and prevent accidents. Fully AV should be available on the EU market by 2030 (ERTRAC, 2017).

2.2. Technology acceptance theories

Practitioners and researchers must know the factors that influence users' decision to use new technologies, including AI-based AVs, in order to take them into account during the development phase (Mathieson, 1991). Technology acceptance models and theories, all of which have their origins in sociology, psychology and communications, have been applied in a wide variety of domains to understand and predict user behaviour. A number of models and frameworks have been developed to explain the user adoption behaviours of new technologies, and these models introduce factors that can affect user acceptance and intention to use. The most used and predominant models are the technology acceptance model (TAM; Davis, 1989; Venkatesh and Bala, 2008; Venkatesh and Davis, 2000) and the unified theory of acceptance and use of technology (UTAUT) model (Kulviwat et al., 2007; Ostrom et al., 2019; Venkatesh et al., 2012). Both the TAM and the UTAUT model have been widely used because of their parsimony and power of explication for the intention of usage of new technologies (King and He, 2006).

The TAM (Davis, 1989) is based on the theory of reasoned action (Fishbein and Ajzen, 1975), which aims to explain the relationship between perceived usefulness and ease of use of a new technology, attitudes (positive or negative predispositions towards the new technology) and behavioural intentions to use (BIU) (an individual's decision to engage or not engage in the behaviour of using a new technology; the most proximal determinant of human social behaviour). An individual's decision to use a particular technology is thus based on a) whether a person believes that using a new technology is free of effort and b) the outcomes the individual expects as a result of performing the behaviour of usage.

The more recent UTAUT model (Venkatesh et al., 2012) includes a consolidation of the constructs of different models developed to explain the user adoption of new technologies. The first is the theory of planned behaviour (Ajzen, 1991) and the TAM (Davis, 1989). Similar to the theory of reasoned action, the theory of planned behaviour considers that attitudes towards a new technology conceptualized through its performance and effort expectancy (in the TAM, this refers to the output benefits of the technology and ease of use), subjective norms (the perceived social pressure to engage or not to engage in a behaviour), and perceived behavioural control (the availability of resources and skills to master the new technology) together shape an individual's behavioural intentions to use it (Carayannis and Turner, 2006; Hernández et al., 2008; Wirtz et al., 2018). The UTAUT model further includes social cognitive theory (Bandura, 1986), which states that an individual's technology knowledge acquisition is directly related to observing others within the context of one's social interactions and experiences. Social cognitive theory is integrated to evaluate new technology usage by using constructs such as self-efficacy and anxiety. Furthermore, the UTAUT model includes the diffusion of innovation theory (Rogers, 1995), which proposes that a social system influences the spread of an innovation. Innovation must be widely adopted by adopters with a high degree of innovativeness, innovators and early adopters to reach a critical mass.

For our research, we choose the UTAUT model (Venkatesh et al., 2011; 2012) and not the TAM (Davis, 1989) since the UTAUT model is more recent, more developed and based on a review and consolidation of the constructs of more theories (King and He, 2006). Based on these theories, we enhance the variables in the UTAUT model by adding user well-being, as consumer well-being has become an important asset in marketing strategies and is attracting increased attention in marketing science research (Sirgy, 2012; Su et al., 2014). Indeed, AVs aim to improve well-being and physical security (Penmetsa et al., 2019; Roca et al., 2009), and connected sensors can help detect variables such as air quality and improve driver security. Furthermore, we integrate affective factors such as social recognition and hedonism into the enhanced UTAUT model (Wirtz et al., 2018), as well as cognitive variables, such as privacy concerns, technology security, and trust in the AV, as they are rarely investigated but relevant key factors for AI-based AV usage (Gefen et al., 2003; Park et al., 2017; Venkatesh et al., 2012).

2.2.1. UTAUT, performance and effort expectancy

Venkatesh et al. (2012) proposed the UTAUT model as the most effective integrated model for analysing technology acceptance and behavioural intention of usage (BIU). BIU refers to the motivational factors that influence a given behaviour, where the stronger the intention to perform the behaviour is, the more likely it is that the behaviour will be performed (Venkatesh et al., 2012). Within the UTAUT model, performance expectancy (PE) and effort expectancy (EE) impact the behavioural intention of usage (BIU) of the new technology (e.g.,Venkatesh et al., 2012). PE refers to users' feelings of improved performance when using a new technology (Gao and Bai, 2014), and EE refers to how a person believes that using a particular technology will free of effort or have a good degree of ease (Venkatesh et al., 2003). PE and EE refer to utilitarian values or benefits (Chaudhuri and Holbrook, 2001). Utilitarian benefits are important aspects when accepting new technologies, including AVs, which are related to cognitive evaluation, product quality, rationality, decision effectiveness, goal orientation, economic value, convenience (e.g., effort and performance expectancy) and drive an individual's BIU (Buckley et al., 2018; Venkatesh et al., 2012). In the case of AVs, previous research has pointed out that some of the most important perceived utilitarian benefits are related to time gain and environmental benefits (Hohenberger et al. 2017; Penmetsa et al., 2019). Hohenberger et al. (2017) suggested that autonomous cars will improve traffic flow and thus reduce travel time, thereby providing users with a time benefit. In addition, drivers should be able to engage in other activities instead of driving, for instance, entertaining themselves or resting, thus saving their time for other tasks. For these reasons, the more users perceive receiving a time benefit from the functions, the more they will be interested in using and exploiting the function to maximize this benefit. Research has also suggested that AVs may also have environmental benefits related to reducing fuel consumption and travel times (Manfreda et al., 2019). Environmental benefits may push consumers to explore and use various functions, thereby representing an approach to improving driving efficiency and signalling their environmental commitment (Shariff and BonnefonIyad, 2017). We thus assume that the perceived time and environmental benefits increase PE and the propensity to use autonomous functions to maximize one's gain. The UTAUT model postulates that EE influences PE and that the actual usage of a technology is determined by its BIU, which is jointly determined by both EE and PE. Thus, the higher the EE is, the more easily AV technology should be used, and the more it should engender a positive experience and capabilities and help users in their daily lives and driving; subsequently, EE should have a positive impact on PE, and PE should have a positive impact on the BIU of AVs (Gao and Bai, 2014; Koul and Eydgahi, 2018). Thus, we posit the following hypotheses:

H1a. The effort expectancy of an AV has a positive effect on its performance expectancy.

H1b. Performance expectancy of an AV has a positive effect on users' behavioural intention to use.

2.2.2. User well-being

Consumer behaviour theory provides evidence that utilitarian value through PE and EE is not sufficient to explain consumer attitudes that affect technology BIU (Chitturi et al., 2008; Hsee et al., 2009). Beyond PE and EE, consumers look for well-being, happiness and other positive emotions while using technologies (Sirgy, 2012; Su et al., 2014). Consumer well-being (WB) is attracting an increased level of attention in academia and transformative marketing science research (Mogilner et al., 2012; Sirgy, 2012; Su et al., 2014). WB is described as the degree to which consumers perceive experiences in positive ways through cognitive judgements and affective reactions without objective facts (Diener, 1984); WB can be linked to physical (Rozanski and Kubzansky, 2005) and mental health (Su et al., 2014), positive moods and emotions, and a pleasant affect, all of which refer to positive emotions (Diener et al., 1985), life satisfaction and quality of life (Ayadi et al., 2017; Diener, 1984; Diener and Chan, 2011).

Research also shows that WB affects consumers' technology choices and usage (Diener and Chan, 2011). Consumers' WB and psychological and physical health may be shaped by using new technologies, such as AI-based AVs (Zhong and Mitchell, 2012), by increasing driver security through automation and sensors, by improving the air quality in the car and by reducing the negative environmental impact (Dhar and Wertenbroch, 2000). Indeed, AVs cope with situations requiring complex observations and interactions, such as highway merging and unprotected left-hand turns, which are challenging for human drivers. For example, over 450,000 lane-change/merging accidents and 1.4 million right-/left-turn accidents occurred in the United States in 2015 alone (National Highway Traffic Safety Administration, 2015). Moreover, according to the same study, one-third of accidents and mortalities could be avoided if vehicles had automation options such as forward collision and lane departure warning systems, side view assistance, automatic braking, and adaptive headlights. Road congestion can be reduced with AVs since they use existing lanes and intersections more competently via shorter gaps between vehicles and the selection of efficient route choices. AVs can also have great ecological benefits related to reducing fuel consumption and greenhouse gas emissions (Greenblatt and Saxena, 2015). Consequently, AVs can increase the level of driver security and thus the physical and psychological WB of drivers through a decrease in perceived risk, which in turn has a positive effect on behavioural outcomes, including AVs' BIU. The higher the level of user-expect WB present when using an AV is, the more the users' positive mental, psychologic and physiologic representations about technology use will be enhanced (Davis and Pechmann, 2013; Spangenberg et al., 2003). Thus, consumers should develop positive feelings towards AI-powered AVs, and WB should positively influence BIU (Spangenberg et al., 2003). Thus, we hypothesize as follows:

H2. Well-being created by an AV has a positive effect on behavioural intention to use.

2.2.3. Social recognition

Social cognitive theory suggests that new technology adoption is impacted by social learning and recognition (Bandura, 1986), which is the degree to which the use of a new product or technology enhances one's social status within a given group (Venkatesh et al., 2012). Social cognitive theory includes the motivations of social pressure in individuals who believe they should use a new technology to obtain a higher social status or a more important position in the groups to which they belong. Social norms, which are defined as the most frequently occurring patterns of overt behaviour for the members of a particular social system, thus have significant effects on new technology usage (Rogers, 1995), as an important motivation for individuals to adopt an innovation or new technology is the desire to gain social status. For certain innovations, the social prestige that the product conveys to its user may be the sole benefit that the adopter receives (Rogers, 1995). Using an innovation such as AI-powered AVs can therefore give social recognition to users through symbolic cues, as well as social status, and should improve one's PE (Gao and Bai, 2014). Adopting AI-powered AVs can be consistent with a group's norms to achieve group membership, social support, well-being and group identification through social image (Sweeney and Soutar, 2001; Venkatesh et al., 2012). Staying up-to-date with these latest technologies allows consumers to convey a certain level of status. In a TAM/UTAUT meta-analysis, Schepers and Wetzels (2007) show the overall influence of subjective norms and social influences on PE and PIU by the existence of an "identification mechanism". Social recognition should thus have a positive influence on AVs' perceived benefits such as PE and thus increase WB. This identification effect is captured in our extended UTAUT model by the effect of social recognition on PE and WB. Accordingly, we hypothesize as follows:

H3. Social recognition due to an AV has a positive effect on a user's performance expectancy.

H4. Social recognition due to an AV has a positive effect on a user's well-being.

2.2.4. Hedonism

Marketers have explored the concept of perceived value, differentiating between utilitarian and hedonic value, from a general point of view (Chitturi et al., 2008). Consumer behaviour research provides evidence that utilitarian value, which is linked with the notion of the cognitive evaluation of product performance and usefulness, has been widely studied, but the research has shown to be insufficient for explaining technology BIU (Chaudhuri and Holbrook, 2001). Research suggests that the hedonic perspective is needed to supplement and extend the marketing research on consumer behaviour. Conversely, hedonic value has been shown to be an important factor of choice (Holbrook and Hirschman, 1982; Hirschman and Holbrook, 1982). It is more subjective and emotional than other factors, and it results more from consumer aesthetics, exploration, fun and entertainment than from task completion (Babin et al., 1994). These pleasing hedonic values or benefits are noninstrumental, experiential and affective. Typically, this hedonic and experiential approach is defined as providing insights into the symbolic, hedonic and aesthetic nature of consumption (Holbrook and Hirschman, 1982). The uses and gratification theory (Katz et al., 1974) further demonstrates that consumers look outside of utilitarian benefits for perceived hedonism and other positive emotions while using technologies (Sirgy, 2012; Su et al., 2014). In other words, hedonic consumption should be taken into account to provide better knowledge about those "facets of consumer behaviour that relate to the multisensory, and emotive aspects of product usage experience." Perceived hedonism, which is related to the concepts of enjoyment and hedonic motivation, is thus defined as fun or pleasure that is derived from using a new technology (Hirschman and Holbrook, 1982; Venkatesh et al., 2012; Wu et al., 2013). Thus, we also propose that when exploring the functions of an autonomous car, consumers also make considerations outside of their utilitarian benefits (e.g., effort and performance expectancy, perceived ease of use and usefulness), i.e., hedonic benefits, such as sensation-seeking and perceived enjoyment (e.g., Herrenkind et al., 2019a; Kapser and Abdelrahman, 2020). Hedonic benefits result more from AV aesthetics, design, driving experience, exploration, fun and entertainment than from task completion (Babin et al., 1994). Previous research has shown that perceived hedonist benefits have an important impact on PE and WB because feeling pleasure is a source of motivation (AgarwalKarahanna, 2000; Gao and Bai, 2014; Spangenberg et al., 2003; Wu and Lu, 2013; Van der Heijden, 2004). Consequently, driving an AV should arouse feelings of experiential fun, pleasure, hedonism, emotions and symbolism and positively impact PE and WB. Thus, we hypothesize as follows:

H5. The perceived hedonism of an AV has a positive effect on users' performance expectancy.

H6. The perceived hedonism of an AV has a positive effect on users' well-being.

2.2.5. Perceived technology security

Technology security is an important challenge that AV manufacturers face (Lijarcio et al., 2019). They need to design systems that can perform safely and handle virtually every possible environmental situation. Recent accidents have initiated concerns regarding drivers' understanding and capability of safely using such technology (Van Brummelen et al., 2018). As an example, Tesla crashes has suggested that AV systems are not sufficiently reliable at this time to allow full automation (Krisher and Durbin, 2016). Slovic (1987) showed that perceived risk is associated with new and unknown technologies, such as AI-based AVs, and may be based on uncertainty or potentially large consequences of technology failure. Consumer decisions to adopt AVs thus involve perceived risk since consequences cannot be anticipated with certainty (Bauer, 1960), as consumers face a set of uncertainties about the purchase of an AV (especially if the product in question is highly priced) (Wang et al., 2020). There are different identified types of perceived risk (Featherman and Pavlou, 2003), namely, functional risk, in which the AV does not perform up to the user's expectations; physical risk, in which the AV poses a threat to the physical well-being or health of the user or others; financial risk, in which the AV is not worth the price paid; social risk, in which the AV results in embarrassment from others; psychological risk, in which the AV affects the uncertainty and mental well-being of the user; and privacy risk, in which data disclosures by the AV threatens the user's private life and well-being. People still perceive risks in putting their safety in the hands of an AV for fear of technical or system failures and malfunctions; there are a few such failure and malfunctions known. Thus, more work needs to be done to fully understand the safety of the human-AV interaction before driving automation can become a reality. Stress can thus be increased through fears regarding AI-based technologies (Koopman and Wagner, 2017).

More precisely, technology security risks for AVs are linked to health risks due to loss of control in the AV, and risks of hacking are sources of potential doubt and stress. This explains the confidence or anxiety that people feel about the safety of using AVs and the extent to which users are willing to rely on such technology (Chaudhuri and Holbrook, 2001). The adoption and usage of an AI-based AV is partly related to concerns over how reliable AVs will be, in addition to uncertainty about how AVs will react in dangerous situations. Many drivers seem unwilling to give up their level of control and thus are less likely to adopt an AV (Asgari and Jin, 2019). Therefore, perceived technology security is an important issue that makes people resist adopting new technology (Kim et al., 2017) and is a recurrent question related to AVs. Indeed, in the case of AVs, previous research has pointed out that one of the most important perceived utilitarian benefits is related to security improvement (Hohenberger et el. 2016). Perceived technology security refers, on the one hand, to how the technology itself reduces human and technology errors, as well as accidents that can harm users' health (Penmetsa et al., 2019). Concerning the security benefits, due to their faster reaction time in comparison to that of humans (Young and Stanton, 2007) and their lower propensity to make mistakes due to distraction, tiredness and poor physical conditions, it is generally assumed that AVs will also reduce accidents, thus providing a safety benefit. On the other hand, perceived technology security refers to mechanisms for avoiding network and data transaction attacks or unauthorized access to user accounts (Roca et al., 2009). Perceived technology security thus refers to the capacity of the AV to be reliable and keep the passengers physically and mentally safe in a given situation. This is especially true of so-called moral dilemma situations, in which it has to be decided (e.g., in the case of an unavoidable collision) which behaviour will cause the least amount of harm to the persons involved both inside and outside the vehicle. We assume that the perceived technology security benefits reduce users' perceptions of their limited abilities to manage, control, and securely drive an AV (Klobas et al., 2019) by decreasing the number of errors and accidents that could harm users' health (McCaul et al., 1993). Therefore, the perceived technology security of AVs should impact user attitudes and perceived behavioural control. If users believe that an AV makes their daily life or driving safer by managing and reducing human errors in complicated or unexpected situations, there should be a positive impact on AV technology trust (Kang et al., 2017; Klobas et al., 2019), which is defined as a positive expectation of a technology, the degree of confidence in that technology, and the belief that one can rely on it (Hernández-Ortega, 2011). By contrast, if users believe that an AV is not completely safe and could lead to dangerous side effects or physical risks due to malfunctions, misuse, or loss of control, then there should be a negative impact on AV technology trust. Therefore, we hypothesize as follows:

H7. The perceived security of AVs has a positive effect on trust in AV technology.

2.2.6. *Perceived privacy concerns*

One antecedent that has been largely studied in technology adoption is the issue of privacy concerns (Xu et al., 2011). Studies have emphasized the importance of security and privacy in AI technology acceptance (Gurumurthy and Kockelman 2020; Tanwar et al., 2017; Panagiotopoulos and Dimitrakopoulos, 2018). Privacy concerns comprise an area of study that is receiving increased attention due to the huge amount of personal information that is currently being gathered, stored, transmitted, and published (Awad and Krishnan, 2006; Hong and Thong, 2013; Cloarec, 2020). Perfect privacy and data protection mechanisms are needed to operate AVs, as the way that AI tracks and collects personal data for customization can seem intrusive and thus arouse privacy concerns (Panagiotopoulos and Dimitrakopoulos, 2018). Privacy concerns are defined as the degree to which users are concerned about the flow and control of the collection, storage and sharing of their personal information (Martin and Murphy 2017; Martin et al., 2017). In the context of AV adoption, privacy refers to the right of individuals to be able to control the compilation, use, and exposure of their data (Gurumurthy and Kockelman 2020; Klobas et al., 2019). In this context, privacy concerns can also relate to a consumer's feeling of risk regarding the disclosure of private data and its use by third parties without that consumer's prior agreement (Kang et al., 2017). Because AVs collect user data such as daily routines, behaviours, and health information, privacy concerns have been identified as one of the greatest barriers to such smart technology acceptance (Malhotra et al., 2004). When users perceive risks regarding the ways in which their data are collected and used by AVs, they tend to develop feelings of stress linked to a lack of control that decrease their trust in that technology (Hong and Thong, 2013). We propose that privacy concerns reduce the level of user trust due to fears related to data privacy and that consumers thus experience an adverse emotional reaction towards AVs that evokes fear and confusion (Gurumurthy and Kockelman 2020). Therefore, we assume that privacy concerns have a negative impact on trust in AI-based AV technologies (Martin and Murphy, 2017), and we hypothesize as follows:

H8. Privacy concerns about an AV have a negative effect on trust in AV technology.

2.2.7. *Technology trust*

Trust can be especially helpful in overcoming the uncertainty that is often present with technological advances; therefore, trust is an important factor of new technology acceptance (Hernández-Ortega, 2011; Pavlou, 2003). Basically, trust in the context of AVs is a three-dimensional factor explaining " […] the individual acceptance of driving assistance systems" (Choi and Ji, 2015; Herrenkind et al., 2019a). The first dimension is concerned with system transparency, which reflects the understanding of how an AV operates. The second dimension is concerned with technical competence, which is the evaluation of an AV's technical performance. The third dimension is concerned with situation management, which refers to the belief in being able to regain control at any time (Lankton et al., 2015). There are two different types of trust in technology, namely, human-like and system-like technology trust (Lankton et al., 2015). Human-like trust is related to integrity, ability, competence, and benevolence, whereas system-like trust refers to reliability, functionality, and helpfulness (Liu et al., 2019) Therefore, in the context of AI and AV, we assume that the more users trust the technology, the more positive the impact on their behavioural intention of use (BIU) and well-being will be (Hernández-Ortega, 2011; Pavlou, 2003). Thus, we hypothesize as follows:

H9. Trust in AV technology has a positive effect on users' well-being.

H10. Trust in AV technology has a positive effect on users' behavioural intention to use.

2.2.8. User innovativeness

User innovativeness refers to the probability of a person being willing to try a new technology (Rogers, 1995). Innovativeness describes a person's "predisposition to purchase new products rather than to remain with previous choices and consumption patterns" (Steenkamp and Gielens, 2003). Hence, customers with high levels of innovativeness are open to change and more likely to take risks (Gilly et al., 2012; König and Neumayr, 2017). Therefore, we consider user innovativeness to be a moderating variable that may enhance the effect of well-being or distress on consumers' intention of use with regard to AVs, and we hypothesize as follows:

H11. User innovativeness enhances the positive effect of performance expectancy on AV behavioural intention to use (H1b).

Place here Fig. 1. Conceptual model about the adoption of AI-powered AV.

3. Data and methodology

3.1. Sample characteristics

Our sample (N = 207) is based on an online survey that was conducted via social networks in France in December 2019. Our survey link to the questionnaire was diffused on Facebook based on the snowball principle. A total of 207 responses were valid for statistical analysis. The gender of our respondents was balanced, with 49% females and 51% males. Furthermore, half of our respondents were less than 33 years old (SD = 0.82); overall, the median age was 27 years. Our sample is thus not representative of the general French population. Samples drawn from younger populations facilitate comparability, and this generation represents a promising market segment for high-technology smart devices, including AVs, since younger generations tend to be more attracted to new technologies and to the Internet than other generations (Ashraf et al., 2014; Barbosa et al., 2018; McMillan and Morrison, 2006).

The questionnaire started with a description of the study's purpose and an explanation of a fully autonomous, level-five, AI-powered vehicle with different decisions made by the AI system with no human intervention required at all. The automated AI-based system takes over all functions and will never need to ask for human intervention. The AV senses the environment and operates without human involvement. It controls the steering, acceleration and deceleration, it monitors the driving environment, and it has a fallback performance, as the driver cannot place his or her hands on the steering wheel (there is no steering wheel). The driver can take his or her eyes off the street and can even sleep. Before answering the survey, the respondents were asked to watch a 5-min video showing this level-five AV.

3.2. Measurement instruments and assessment of the measurement model

All measurement scales were based on and adapted from previous studies. Responses were collected based on a seven-point Likert scale (1 = fully disagree, 7 = fully agree). The full-scale items can be seen in Table 1.

User well-being (e.g., "WB1: If I used this AV, my life quality would be improved to ideal; WB2: If I used this AV, my well-being would improve; WB3: If I used this AV, I would feel happier") was measured with the scales from Diener and Chan (2011).

To measure perceived hedonism (e.g., "PH1: Using this AV would give me joy; PH2: Using this AV would be fun, PH3: Using this AV would be amusing"), we adapted scales from Sweeney and Soutar (2001). For social recognition (e.g., "SR1: This AV would give me a more acceptable image of myself; SR2: This AV would improve how my friends and family perceive me; SR3: This AV would give me better social recognition"), we also used a scale adapted from Sweeney and Soutar (2001).

Privacy concerns (e.g., "PC1: I would be concerned about threats to my personal privacy from this AV; PC2: I would be afraid of using this AV because cyber pirates might steal my identity and data.; PC3: I would be afraid to use this AV because other people might cyberstalk me; PC4: I would be afraid of this AV collecting too much of my personal data; PC5: I would be afraid of using this AV because other people or firms might publish my personal information without my consent; PC6: I would be afraid of using this AV because it might insufficiently protect my personal data; PC7: I would be afraid to use this AV because it might track and analyse my personal data for personalized offers; PC8: I would be afraid to use this AV because it might share personal data with other firms for purposes I do not know about") were measured with a scale taken from Hong and Thong (2013).

Perceived technology security (e.g., "PTS1: This AV would help make my journeys safer; PTS2: This AV would manage complicated or unexpected traffic situations better than me; PTS3: This AV would help to reduce human driver mistakes in complicated or unexpected situations") was measured with a scale from Lijarcio et al. (2019).

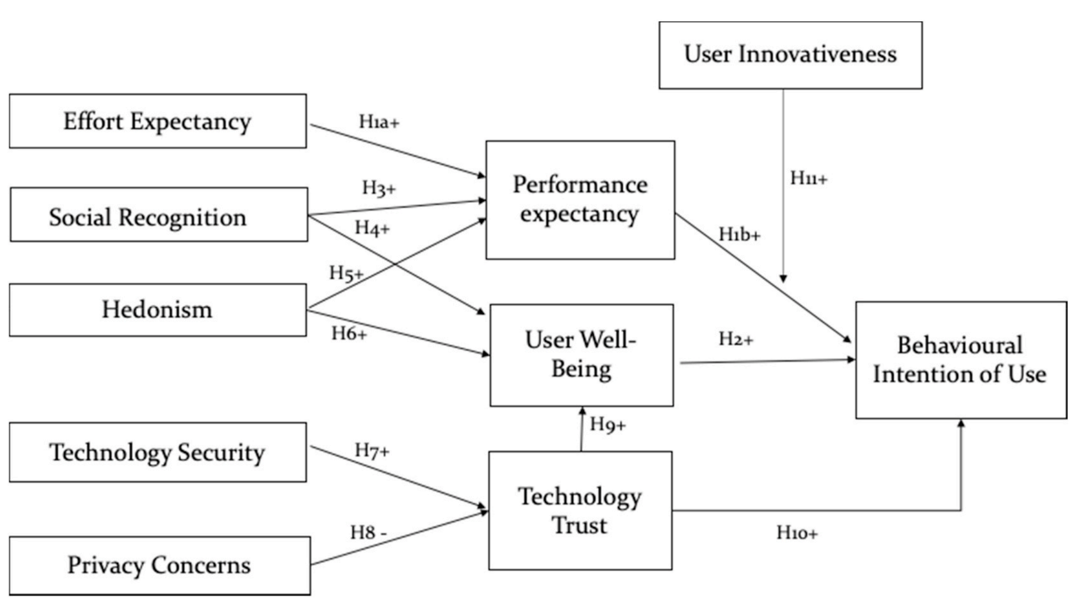

Fig. 1. Conceptual model about the adoption of AI-powered AV.

Table 1
Reliability (α and ρ) and convergent validity.

Constructs	α	ρ	Conv. val.	Loadings
User Well-Being (Diener and Chan, 2011)	0.936	0.938	0.834	
WB1: If I used this AV my life quality would be improved to ideal.				0.919
WB2: If I used this AV my well-being would improve.				0.942
WB3: If I used this AV, I would feel happier.				0.877
Hedonism (Sweeney and Soutar 2001)	0.887	0.884	0.719	
PH1: Using this AV would give me joy.				0.945
PH2: Using this AV would be fun.				0.811
PH3: Using this AV would be amusing				0.778
Social Recognition (Sweeney and Soutar 2001)	0.930	0.933	0.823	
SR1: This AV would give me a more acceptable image of myself.				0.876
SR2: This AV would improve how my friends and family perceive me				0.942
SR3: This AV would give me better social recognition.				0.902
Privacy Concerns (Hong and Thong 2013)	0.943	0.944	0.683	
PC1: I would be concerned about threats to my personal privacy from this AV				0.682
PC2: I would be afraid of using this AV because cyber pirates might steal my identity and data.				0.793
PC3: I would be afraid to use this AV because other people might cyberstalk me.				0.625
PC4: I would be afraid of this AV collecting too much of my personal data.				0.890
PC5: I would be afraid of using this AV because other people or firms might publish my personal information without my consent.				0.890
PC6: I would be afraid of using this AV because it might insufficiently protect my personal data.				0.930
PC7: I would be afraid to use this AV because it might track and analyse my personal data for personalized offers.				0.882
PC8: I would be afraid to use this AV because it might share personal data with other firms for purposes I don't know about.				0.868
Technology Security (Lijarcio et al., 2019)	0.888	0.887	0.724	
PTS1: This AV would help make my journeys safer.				0.861
PTS2: This AV would manage complicated or unexpected traffic situations better than me.				0.860
PTS3: This AV would help to reduce human driver mistakes in complicated or unexpected situations.				0.832
Technology Trust (Morgan and Hunt, 1994)	0.949	0.950	0.826	
TT1: I think that this AV would provide 100% reliable services.				0.893
TT2: I think this AV would not fail me.				0.851
TT3: I think this AV would be 100% trustworthy.				0.949
TT4: I would totally trust this AV.				0.940
Effort Expectancy (Venkatesh et al., 2012)	0.885	0.886	0.722	
EE1: I would find this AV easy to use.				0.884
EE2: I would find it easy to become skilful at using this AV.				0.866
EE3: I would learn quickly how to use this AV.				0.796
Performance Expectancy (Venkatesh et al., 2012)	0.958	0.959	0.853	
PE1: This AV would be a good assistant in my daily life.				0.927
PE2: This AV would help me save useful time in my daily life.				0.921
PE3: This AV would make my everyday driving life easier.				0.939
PE4: This AV would increase my efficiency in my daily driving life.				0.906
Behavioural Intention to Use (Venkatesh et al., 2012)	0.934	0.946	0.855	
BIU1: Looking at its benefits, I intend to buy this AV in the future.				0.943
BIU2: Looking at its benefits, if I had access to this AV I would intend to buy it.				0.944
BIU3: The probability that I buy this AV in the future is:				0.885
User Innovativeness (Steenkamp and Gielens, 2003)	0.791	0.819	0.694	
INO1: If I hear about a new technology, I like to try it out.				0.878
INO2: I am usually the first one in my surroundings to use a new technology.				0.785

Technology trust (e.g., "TT1: I think that this AV would provide 100% reliable services; TT2: I think this AV would not fail me; TT3: I think this AV would be 100% trustworthy; TT4: I would totally trust this AV") was measured with the scale from Morgan and Hunt (1994).

To measure effort expectancy (e.g., "EE1: I would find this AV easy to use; EE2: I would find it easy to become skilful at using this AV; EE3: I would learn quickly how to use this AV"), as well as performance expectancy (e.g., "PE1: This AV would be a good assistant in my daily life; PE2: This AV would help me save useful time in my daily life; PE3: This AV would make my everyday driving life easier; PE4: This AV would increase my efficiency in my daily driving life") and behavioural intention to use (e.g., "BIU1: Looking at its benefits, I intend to buy this AV in the future; BIU2: Looking at its benefits, if I had access to this AV I would intend to buy it; BIU3: The probability that I will buy this AV in the future is (from 0 to 100%)"), we used the UTAUT scales from Venkatesh et al. (2012).

Finally, user innovativeness (e.g.," INO1: If I hear about a new technology, I like to try it out; INO2: I am usually the first one in my surroundings to use a new technology") was measured with a scale adapted from Steenkamp and Gielens (2003).

We conducted exploratory and confirmatory factor analyses to test for the reliability and validity of the measurement instruments. During the scale validation process, we kept all items. According to the literature standards (Fornell and Larcker, 1981), the results offered satisfactory psychometric properties for reliability (Cronbach's alpha and Joreskog'ρ greater than the 0.7 threshold; Nunnally, 1967) and convergent validity (ρ_{vc} around or above 0.5). Table 1 shows the scale reliabilities and convergent validity values. The correlation between constructs was less than the square root of the average variance extracted ($r^2 <$ convergent validity), which is indicated on the diagonal and signals discriminant validity (Bagozzi and Yi, 1988; Fornell and Larker, 1981). Table 2 presents the means (M) standard deviations (SD) for the scales used for measurement related to the assessment of discriminant validity.

The measurement model achieved good fit according to the usual fit indices: the chi-square/df ($\chi2$/df) was less than 2.5; the comparative fit index (CFI) was greater than 0.90; and the root mean square error of approximation (RMSEA) was not greater than 0.08 (Anderson and Gerbing, 1988). The fit indices of the measurement model are summarized in Table 3.

Table 2
Discriminant validity.

	M	SD	PH	SR	PC	TS	TT	EE	PE	WB	BIU	INO
PH	4.3	1.6	0.79									
SR	2.6	1.7	0.14	0.83								
PC	4.1	1.4	0.06	0,01	0.683							
TS	4.9	1.7	0.29	0.16	0.029	0.74						
TT	3.1	1.8	0.22	0.16	0.073	0.44	0.826					
EE	5.8	1.7	0.11	0.05	0.079	0.11	0.185	0.72				
PE	4.0	1.7	0.41	0.12	0.046	0.49	0.306	0.20	0.83			
WB	3.6	1.9	0.33	0.32	0.025	0.38	0.356	0.17	0.69	0.834		
BIU	3.3	2.2	0.40	0.26	0.057	0.38	0.375	0.28	0.52	0.476	0.85	
INO	4.7	1.0	0.18	0.13	0.043	0.05	0.122	0.14	0.21	0.214	0.36	0.64

EE*: Effort expectancy,* PE*: Performance expectancy,* SR*: Social Recognition,* WB*: Well Being,* PH*: Perceived Hedonism,* PC*: Privacy Concerns,* TT*: Technology Trust,* TS*: Technology Security,* BIU*: Behavioural Intention to Use,* INO*: User Innovativeness.*

Table 3
Measurement model fit indices.

χ^2	df	RMSEA	CFI	TLI
985	549	0.0620	0.943	0.934

4. Results

4.1. Results structural equation model

To test the hypotheses, we conducted multigroup structural equation modelling (SEM) and mediation analysis using the software R 3.6.1 and the lavaan package (Rosseel, 2012). Table 4 shows the fit indices for the structural equation model, which again achieved good fit (RMSEA < 0.08, CFI > 0.90, and TLI > 0.90).

Table 5 shows the results of the SEM. Effort expectancy of AVs has a positive and significant effect on performance expectancy (β = 0.163, p < 0.005). Thus, H1a is supported. In turn, the performance expectancy of AI-based AVs has a positive and significant effect on the behavioural intention to use AVs (β = 0.501, p < 0.000). Thus, H1b is supported. Well-being created by an AV has a positive effect on the behavioural intention to use (β = 0.178, p < 0.010). Thus, H2 is supported. The social recognition of AI-based AVs has no significant effect on performance expectancy (β = 0.068, p > 0.221), but it does have a significant and positive effect on well-being (β = 0.253, p < 0.000). Thus, H3 is rejected, while H4 is supported. The perceived hedonism of AI-based AVs has a positive and significant effect on both performance expectancy (β = 0.704, p < 0.000) and well-being (β = 0.503, p < 0.000). Thus, H5 and H6 are both supported. Moreover, technology security and privacy concerns have significant positive (β = 0.694, p < 0.000) and negative (β = -0.158, p < 0.005) effects, respectively, on AV technology trust. Thus, both H7 and H8 are supported. Trust in AI-based AV technology has a positive and significant effect on well-being due to an AV (β = 0.242, p < 0.000). Thus, H9 is supported. Finally, trust in AI-based AV technology has a positive effect on the behavioural intention to use AI-based AVs (β = 0.272, p < 0.000). Thus, H10 is supported.

4.2. Mediation analyses

We carried out a mediation analysis with 1000 bootstrap samples (Hayes 2009). The results show three significant mediating effects (the 95% confidence interval [CI] excludes 0; Table 6).

First, there is a significant indirect positive effect that runs from perceived hedonism to the behavioural intention to use via performance expectancy (β = 0.3525, p < 0.05, 95% CI [0.1447; 0.5603]). Second, there is a significant indirect negative effect that runs from privacy concerns to behavioural intention to use via trust in AV technology (β = −0.043, p < 0.05, 95% CI [-0.0856;-0.004]). Third, there is a significant positive effect running from perceived technology security to behavioural intention to use via trust in AV technology (β = 0.1887, *p* < 0.05, 95% CI [0.0671; 0.3103]).

Finally, user innovativeness moderates the link between performance expectancy and the behavioural intention to use an AV, as hypothesized in H1b (p < 0.001 < 0.05). This means that the more innovative the user is, the more their performance expectancy will positively impact their behavioural intention to use an AV. We thus confirm H11.

Table 4
Structural equation model fit indices.

χ^2	df	RMSEA	CFI	TLI
1074	506	0.074	0.923	0.914

Table 5
Results structural equation model.

	β	p
H1a: EE → PE	0.163	0.005
H1B: PE → BIU	0.501	<0.000
H2: WB → BIU	0.178	0.010
H3: SR → PE	0.068	0.221
H4: SR → WB	0.253	<0.000
H5: PH → PE	0.704	<0.000
H6: PH → WB	0.503	<0.000
H7: TS → TT	0.694	<0.000
H8: PC → TT	−0.158	0.005
H9: TT → WB	0.242	<0.000
H10: TT → BIU	0.272	<0.000

EE*: Effort expectancy,* PE*: Performance expectancy,* SR*: Social Recognition,* WB*: Well Being,* PH*: Perceived Hedonism,* PC*: Privacy Concerns,* TT*: Technology Trust,* TS*: Technology Security,* BIU*: Behavioural Intention to Use.*

Table 6
Results mediation analysis.

Mediation	β	95% CI		Significant
		Lower	Upper	
EE → PE → BIU	0.0814	−0.0365	0.1992	No
SR → PE → BIU	0.0341	−0.0758	0.144	No
SR → WB → BIU	0.0451	−0.019	0.1092	No
PH → PE → BIU	0.3525	0.1447	0.5603	Yes
PH → WB → BIU	0.0894	−0.036	0.2148	No
PC → TT → BIU	−0.043	−0.0856	−0.0004	Yes
TS → TT → BIU	0.1887	0.0671	0.3103	Yes
TS → TT → WB → BIU	−0.0068	−0.0182	0.0046	No
TS → TT → WB → BIU	0.0299	−0.0145	0.0543	No

EE*: Effort expectancy,* PE*: Performance expectancy,* SR*: Social Recognition,* WB*: Well Being,* PH*: Perceived Hedonism,* PC*: Privacy Concerns,* TT*: Technology Trust,* TS*: Technology Security,* BIU*: Behavioural Intention to Use.*

5. Discussion

5.1. Discussion of the results and theoretical implications

Technology acceptance models such as TAM or the UTAUT model (e.g., Davis, 1989; Venkatesh et al., 2012) have contributed significantly to the understanding of the adoption process of new technologies. Nevertheless, they typically focus on variables that belong to the perceptions of AVs (e.g., perceived usefulness and benefit, performance expectancy, perceived ease of use, effort expectancy). This research extends the current understanding of AI-based AV adoption by uncovering the roles of rarely investigated or unelaborated antecedents, mediators and consequences. Cognitive, social and affective variables have received less attention in studies about AVs that build on the TAM and the UTAUT model. Our study therefore contributes to enriching the AV technology acceptance and innovation literature and to enhancing the UTAUT model by adding new or rarely investigated key determinants that are relevant to the behavioural intention to use AI-powered AVs], namely, social influence, cognitive processes about perceived utilitarian (effort- and performance expectancy) and hedonic benefits, privacy concerns, perceived technology security, trust, and affective factors, namely, user well-being. We thus extend the model by adding new or rarely tested constructs. Among the antecedents, hedonic benefits have already been confirmed (Kapser and Abdelrahman, 2020); however, the two motivations, hedonic and utilitarian, which play key roles in users' choices, have not been considered in the context of AV adoption. This study sheds further light on the understanding of other cognitive variables, namely, technology security. We have confirmed the positive effects of AV-related technology security on the behavioural intention to use AV (Herrenkind et al., 2019a, b; Hohenberger et al., 2016). Furthermore, we have shown the negative influence of data privacy concerns in the adoption process, about which even less is known. This study sheds further light on the understanding of the underinvestigated variables related to affective states, namely, user well-being. Finally, this study contributes to an understanding of the expected social outcomes of the behavioural intention to use AV (Gao and Bai, 2014; Schepers and Wetzels, 2007; Venkatesh et al., 2012).

When first interacting with a new technology, such as AI-based AVs, users determine its expected positive and negative consequences. Thus, considering that new technologies, including AVs, are often complex, users assess them at the same time as the related potential benefits or opportunities and risks or threats (Venkatesh et al., 2012). Perceived opportunities are derived from the association with new AV technology (Bala and Venkatesh, 2015).

Our results are in line with previous findings about the importance of the concepts of cognitive variables in AI-powered AV usage (King and He, 2006; Venkatesh et al., 2012). Among the cognitive variables, perceived utilitarian and hedonic benefits play important roles while using AV and positively influence the behavioural intention to use AI-based AVs (Chen and Yan, 2019; Lee et al., 2019). First, effort expectancy has a direct positive effect on performance expectancy (Sener et al., 2019; Venkatesh and Davis, 2000). Second, performance expectancy has a positive effect on the behavioural intention to use AI-based AVs (e.g., Hegner et al., 2019; Madigan et al., 2017; Sener et al., 2019; Venkatesh et al., 2012; Zmud et al., 2016). Motivations linked to hedonism (Kapser and Abdelrahman, 2020; Madigan et al., 2017), sensation-seeking and perceived enjoyment (Herrenkind et al., 2019a) positively influence the behavioural intention to use AI-based AVs. A significant indirect positive effect runs from perceived hedonism to the behavioural intention to use AI-based AVs (Gao and Bai, 2014; Hu et al., 2003; Van der Heijden, 2004) via performance expectancy (Venkatesh et al., 2012). In line with the literature, the perceived hedonism of an AV also has a positive impact on well-being (Childers et al., 2001; Sweeney and Soutar, 2001; Van der Heijden, 2004). Thus, hedonic and utilitarian benefits are fundamental to understanding consumer behaviours, including AV usage (Childers et al., 2001). Hence, the benefit of hedonic motivation is experiential and emotional (Babin et al., 1994; Hirschman and Holbrook, 1982), whereas utilitarian motivation is rational, decision effective, and goal oriented (e.g., effort and performance expectancy). Hedonic customers seek novel, varied, and complex sensational experiences and are willing to take risks; thus, they are more likely to accept the novelty and risks associated with self-driving cars (Osswald et al., 2012). Consumers thus follow different decision-making paths when adopting an AV, i.e., either "problem solving" or the seeking of "fun, fantasy, arousal, sensory stimulation, and enjoyment" (Holbrook and Hirschman, 1982). Hedonic benefits are specifically found to be a predictor of key importance (Madigan et al., 2017). According to our results, hedonic benefits are more than seven times as impactful as utilitarian benefits. This is a new insight because both utilitarian and hedonic benefits as a direct antecedent of performance expectancy have not yet been investigated. We thus contribute to the AV technology adoption literature, as neither utilitarian nor hedonic motivation has been previously investigated. Research shows that new technologies can be used both for fun (i.e., hedonic motivation) and productivity (i.e., utilitarian motivation) and that fun can be as or even more important than productivity for many users. When users start to adopt a particular new technology, such as AVs, 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).

The second group of cognitive variables and antecedents is related to technology security, privacy concerns and trust towards AVs. AV technology trust is one of the most important variables, as it positively influences well-being and the behavioural intention to use AI-based AVs (Hegner et al., 2019; Hernández-Ortega, 2011; Herrenkind et al., 2019a, 2019b; Hohenberger et al., 2016; Liu et al., 2019; Panagiotopoulos and Dimitrakopoulos, 2018; Pavlou, 2003; Zmud et al., 2016). In turn, technology anxiety, which is the tendency of users to be uneasy, apprehensive, or fearful about using innovative technologies due to a lack of usage experience (Sääksjärv and Samiee, 2011), decreases behavioural intention to use AI-based AVs (Hohenberger et al., 2016; Zmud et al., 2016).

In line with the literature, technology security is another important factor, as there is a significant strong positive effect running to the behavioural intention to use via its positive impact on trust in AI-based AV technologies and user well-being (Hernández-Ortega, 2011; Hoffman et al., 1999; Kang et al., 2017; Klobas et al., 2019; Kapser and Abdelrahman, 2020; Liu et al., 2019; Montoro et al., 2019; Zmud et al., 2016). On the other hand, there is a significant indirect negative effect that runs from privacy concerns to the behavioural intention to use via trust in AI-based AV technologies (Panagiotopoulos and Dimitrakopoulos, 2018; Hong and Thong, 2013). Privacy concerns refer to a user's vulnerability due to their loss of control over the management of their personal information by firms (Martin et al., 2017). Indeed, data privacy concerns are an important barrier in our research model, and data security is a highly important theme. In our study, data privacy concerns have a significant negative effect, whereas technology security has a positive effect on technology trust and behavioural intention to use AI-based AV technologies. To increase trust, users prefer a data-secure AV that is under their control and no technology risk. Individuals thus intend to use AVs when the related IT provides data privacy and security protection (Panagiotopoulos and Dimitrakopoulos, 2018). The most severe concern stems from potential safety issues caused by the fear of attacks by hackers (König and Neumayr, 2017). According to a survey, 93 percent of US and European citizens have privacy concerns about identity theft and fraud (Clement, 2019). Perfect technology security, privacy and data protection mechanism are needed to increase trust in AV technology and decrease feelings of stress, as the way that AI tracks and collects personal data for customization can seem intrusive and arouse privacy concerns, as well as a lack of control (Awad and Krishnan, 2006; Hong and Thong, 2013; Malhotra et al., 2004). Thus, higher levels of technology and privacy security related to AVs leads to significantly more technology trust, which, in turn, significantly and positively affects users' well-being and ultimately their behavioural intention to use.

The third group of antecedents is related to affective states towards AI-powered AV usage (Diener and Chan, 2011). We highlight the importance of the link between user well-being and AI-powered AV adoption and usage (Diener et al., 1985). Thus, our main contribution is that in the AI and AV technology acceptance process, well-being is an extremely important concept (Diener and Chan, 2011), as using AV with psychological and physical health features should improve users' well-being (Dhar and Wertenbroch, 2000; Spangenberg et al., 2003; Van der Heijden, 2004). The more that users expect well-being when using an AV, the more they will develop positive feelings towards the AI-powered AV, and the more they should intend to use this technology (Dhar and Wertenbroch, 2000; Spangenberg et al., 2003).

The fourth group of antecedents is related to the social environment (e.g., social norms and social influence (e.g., Kapser and Abdelrahman, 2020), which positively influences the behavioural intention to use. In line with the literature, social recognition has a positive influence on driver well-being (Schepers and Wetzels, 2007).

Finally, the positive role of individual innovativeness, which is a personality trait defined as the willingness of an individual to try out any new information technology (Agarwal and Prasad, 1998), has been shown, as it moderates the link between performance expectancy and behavioural intention to use AVs (Chen and Yan, 2019; Hegner et al., 2019; Sener et al., 2019). Hence, the probability that a consumer tries new technologies such as an AV is higher for innovative users than for noninnovative users (Steenkamp and Gielens, 2003). Therefore, users with high levels of innovativeness are more accustomed to using new technologies. This differential effect may be explained by innovative users' prior knowledge. Such users are more knowledgeable about technology-related topics; hence, their level of perceived technological anxiety is lower, and they have a deeper knowledge of the potential benefits of AV technologies, which leads to an underestimation of the negative consequences of risks.

In summary, our results show that well-being, perceived hedonism and trust have the strongest effects on the behavioural intention to use AVs. In addition, the perceived risk of AI-based AV technologies has a negative influence on trust, which is another key concept, and thus on AV adoption. Thus, users seek effective AV features based on technology security and privacy protection rather than on highly advanced, automated, and less-controllable vehicles. To increase trust, users are likely to prefer a data-secure AV that is under their own control and to avoid the technology risks related to a fully automated AV.

5.2. Managerial implications

Our conceptual model provides managers with an overview of which factors affect the behavioural intention to use AVs. This framework is highly relevant from a managerial perspective, as it provides insights and recommendations to increase users' intentions to use autonomous cars. We recommend that managers focus on the following key variables: AV users' perceived hedonism, perceived technology security, technology trust and, consequently, well-being. Furthermore, managers should focus on privacy concerns that are currently at the top of the managerial agenda.

A major antecedent to using AI-based AVs is perceived hedonism, which has an impact on both user well-being and performance expectancy. For example, hedonic motivation, sensation-seeking, and enjoyment all demonstrate that it is important to highlight these types of motivations in communication by emphasizing how much fun it is to travel when using such vehicles. Thus, the interior of autonomous cars must be designed to increase users' well-being and make the vehicle more pleasing to customers. On the hand, sensation-seeking and enjoyment can be communicated through the driving capabilities of AVs. Performance expectancy is also an important criterion for consumers to use AVs. This relates to rational utilitarian motivation based on goal-oriented product quality, economic value, convenience and driving performance (e.g., effort- and performance expectancy). In the case of AVs, managers should focus on the communication of the utilitarian benefits related to driving efficiency and time gain, as autonomous cars might improve traffic flow and reduce travel time. In addition, managers should show that drivers will be able to engage in other activities instead of driving, for instance, entertaining themselves or resting, thus saving their time for other tasks. For these reasons, the more that users perceive themselves as gaining a time benefit from the AV functions, the more they will be interested in using and exploiting AVs to maximize this benefit. The communication of environmental benefits by showing reduced fuel consumption may represent a way of signalling users' environmental commitment.

On the other hand, increasing fears about security are important barriers to AI-based AV acceptance. Affective states, such as trust and technology security, as well as user well-being, can be directly influenced by AV marketing managers. Therefore, it is vital to increase trust and decrease fears through communication about technology security. Therefore, businesses should take into consideration perceived technology security to show the public that their vehicles are safe in order to increase the public's trust towards their products or services. Perceived technology security is considered a key factor because it impacts trust towards AI-based AV technologies in a positive way. Thus, marketing managers should show with rational figures that AVs are overall safe to use. Trust in AV service providers has become a significant issue, as data-based AV companies such as Google are rapidly expanding in this sector. Managers should increase AV security and reliability, while AV service providers should apply high-level security technologies to prevent data sharing and leakage. Increasing safety communication is therefore an essential point, and managers should try to reassure and highlight the related benefits in terms of technology and data safety, in particular, the 95% of accidents that are caused by human error.

Our study also shows the importance of privacy concerns. Indeed, data privacy concerns are an important barrier regarding trust in AV technology because data security is an increasingly important issue worldwide, with the most severe concerns being identity theft and fraud (Clement, 2019). AV managers thus have to work on data management devices that are difficult to hack in order to decrease data privacy concerns due to the loss of control over the management of one's personal information (Martin et al., 2017). Furthermore, organizations have to restrict the commercialization of user data to other firms. Specifically, only opt-in data sharing should be used (e.g., the process used when a positive action of the consumer is required to use his/her data).

Furthermore, a high level of trust leads to greater levels of consumer well-being, which is a direct antecedent to AV adoption and usage. Indeed, well-being constitutes another core concept leading to AV usage. The more that potential users think that an AV would make them happier and increase their well-being, the likelier they are to use such cars. For managers, this implies focusing on a comparatively small number of concepts that are encompassed by well-being regarding the use of AVs. Hence, managers must be aware of the fact that customers expect to drive better, more easily and more happily by means of new technologies, including AI-based AVs, which simplify their lives, increase their quality of life, and decrease distress caused by feelings of insecurity and stress. Thus, marketing managers must show with illustrative data how AVs can increase user well-being by reducing driving errors and thus driver health by freeing up driving time to do other relaxing activities, improving air quality in the cabin, and reducing pollution and thus cognitive dissonance (Festinger, 1957). Beyond that, information- and awareness-raising campaigns could increase the social recognition of AV users and thus their well-being.

Finally, there is a positive interaction between user innovativeness, performance expectancy and the intention to use AI-based AVs. Users who are more open to innovations are more likely to consider performance expectancy as an important criterion for AVs, which in turn influences their purchase decisions. Our empirical research thus implies that personality trait-related variables are relevant for segmentation, as highly innovative and less innovative consumers may be affected by different factors. User innovativeness as a segmentation variable can provide insight into the aspects of advertising that should be emphasized. This also highlights the need to target innovative special advertising arguments that lead users to be more open to the technological innovation of AVs. In contrast, users who belong to the group of technological laggards should be addressed by placing emphasis on other arguments. Based on this result, we recommend that managers use these observations for their specific segmentation and targeting strategies.

6. Limitations and future research directions

Although the findings of this study provide meaningful insights into both the light and dark sides of AI-based AVs, certain limitations must be addressed. First, the sample size is relatively small and comes only from France and may thus not be perfectly representative. Nevertheless, we do not believe that the specific cultural and social context of France affects users' acceptance of AV technologies. First, AV technologies are advanced but not standardized and are thus not truly subject to cultural influences (Ashraf et al., 2014). Second, we have seen in the discussion section that our results are mostly in line with the existing studies about AVs, which have largely been realized in economically developed Western countries (Payre et al., 2014 in France; Hohenberger et al., 2016, Herrenkind et al., 2019 a,b, Kapser and Abdelrahman, 2020, in Germany; Montoro et al., 2019 in Spain; Zmud et al., 2016 in the US) and mostly based on (as in our research) nonrepresentative or convenience samples. Nevertheless, future studies should use larger and more representative professional panel provider samples to ensure the generalizability of the results. Second, research on AI-based AV technology acceptance is still limited (Fraedrich and Lenz, 2016). Therefore, future research should work to understand acceptance phenomena from a social and ethical perspective by integrating aspects of MIT's moral machine (Awad et al., 2018). Moreover, our conceptualization of well-being proves to be oversimplified (Diener and Chan, 2011). Other more detailed dimensions of psychological, physical, financial well-being should be conceptualized in future studies. Fourth, the model could be enhanced with additional variables, such as other types of risks (e.g., price and financial risks) and benefits (e.g., the visual attractiveness of the design). Fifth, the respondents expressed their views only on AI-powered AVs after watching a short video but had not yet used AV and thus might have biased a priori perceptions and attitudes towards AVs. The video might not have provided the respondents with enough information to fully understand all the benefits and risks of AVs. Unfortunately, we could not control these a priori perceptions and attitudes (as is the case in most academic studies about new products, services and technologies). Hence, further research is needed to control these a priori perceived risks and benefits and to gain a more in-depth understanding of how perceptions of AVs shape the behavioural intention to use AVs. Future studies should thus be carried out with innovative methodological approaches, with real level-2 AVs and level-5 virtual reality and simulation (such as that of the fully automated car that should be available on the EU market by 2030) and put respondents in actual real-life use situations.

7. Conclusion

This research provides a literature review of the extant studies on AI-based AVs and empirically tests new antecedents, mediators and consequences that have previously not been investigated or have been investigated in only a few prior studies. Our findings offer important insights for practice and academia to increase the adoption of AVs.

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