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Opening the moral machine's cover: How algorithmic aversion shapes autonomous vehicle adoption

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ABSTRACT

Autonomous driving technology has made its way into the market at various levels, yet fully autonomous vehicles remain unavailable. The psychological barriers that must be overcome before fully automated vehicles (AVs) become mainstream are numerous. In addition to technological advancements, persuading consumers to transition from the traditional human-driven model to AVs poses a significant challenge. According to the Moral Machine Experiment, Latin American countries form distinct sub-clusters and exhibit the highest preference for action in moral decision-making. To foster user acceptance of AVs in these countries, it is imperative to comprehend cognitive, affective, and ethical factors. To this end, we conducted experiments with respondents from Colombia to examine how varying levels of automation influence algorithm aversion and user acceptance. Algorithm aversion is explored from two perspectives: ethical judgment and behavior, and emergency evaluation and performance. Our findings reveal two key insights. Firstly, higher levels of automation negatively impact people's assessment of the emergency evaluation capabilities of AVs, partially contributing to algorithm aversion. Secondly, the intention to use AVs is adversely affected by algorithm aversion, encompassing both ethical considerations and emergency performance-related aspects. Furthermore, mediation analysis demonstrates that perceived hedonism elucidates the inverse relationship between algorithm aversion and the intention to use AVs.

1. Introduction

Autonomous vehicles (AVs) are widely recognized as the next technological revolution by researchers (Bennett et al., 2019), top consulting firms (Bertoncello & Wee, 2015; Silberg, 2017) and industry leaders. However, at present, widespread adoption of driverless cars is taking longer than expected (NY Times, 2019). Initial deployment of highly autonomous vehicles and related mobility services (i.e., robotaxis) was prematurely targeted for such machines to be commonplace on highways in the early 2020s (Faggella, 2020). To support these ambitions, automakers and tech companies have invested billions in autonomous driving (Goh & Yilei, 2020). Despite these investments and bold claims from industry leaders, several launches of fully self-operating vehicles have been continuously postponed or scaled back (Doll et al., 2020). Today, autonomous driving technology has been introduced into the market at

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varying levels but not yet for fully autonomous vehicles (Adnan et al., 2018). Moreover, partially autonomous vehicles that are already on some roads still seem to need some work to improve their safety, especially with unpredictable occurrences (NY Times, 2019). Although driverless technology has yet to be refined, it is expected that AVs will mature quickly over the next decade (Bloomberg Hyperdrive, 2020). The global sales of vehicles with at least Level 3 autonomy (also called conditional automation, where only specific tasks are performed autonomously) are projected to reach a value of approximately 58 million units in 2030, versus the 1.4 million that were estimated to be sold worldwide in 2019 (Statista, 2021a). Moreover, Statista's most recent reports state that over 40 percent of customers worldwide would be willing to use fully autonomous or semiautonomous cars (Statista, 2021b).

Before AVs go mainstream, the industry has yet to overcome various challenges. Alongside the projected growth in sales for AVs in the coming decade, Statista also proposes that the technological aspect is not the only hurdle to overcome for AVs to take off (Statista, 2021b). In their latest report, they bring to light that more than half of the customers are worried about the safety of autonomous cars and over 30 percent are not sure whether the technologies necessary for autonomous vehicles to operate are advanced enough (Statista, 2021b). To date, there seems to be no consensus between the general public, policy makers and AV developers on how safe AVs must be before they can be deployed (Goodall, 2021). In line with this perspective, the literature on AV research acknowledges that despite the evident advantages, challenges persist, particularly in persuading consumers to transition from the traditional human-driver model to autonomous cars (Adnan et al., 2018). This necessitates articulating accurate expectations for users and the general public, as expectations play a crucial role in market acceptance and adoption (Lin, 2016).

Shariff et al. (2017) suggest "*the biggest roadblocks standing in the path of mass adoption [of self-driving cars] may be psychological*" (p. 694). Social and cognitive factors should also be understood to analyze user acceptance of AVs (Meyer-Waarden & Cloarec, 2022). Thus, technical R&D investments made by automakers and tech companies are only one component to ensure widespread acceptance of AVs. It is fundamental to measure and better understand customer needs and variables that influence the adoption of AVs (Meyer-Waarden & Cloarec, 2022; Nastjuk et al., 2020; Panagiotopoulos & Dimitrakopoulos, 2018; Xu et al., 2018), especially given their nature of radical innovation (Keszey, 2020). Several studies have researched the variables expected to influence the forthcoming adoption of AVs. To depict a comprehensive view of the variables investigated in prior studies, Keszey (2020) conducted a systematic review of empirical studies on the acceptance of AVs, specifically on the antecedents and outcomes of behavioral intention to use. The *meta*-framework resulting from this review proposes five main categories of antecedents of behavioral intention to use (i.e., personality traits, emotional states, perceptions, social environment, and descriptive variables). Within this classification, hedonic motivation is found to be a predictor of key importance (Keszey, 2020). In addition to these antecedents, the ethical implications of AVs have been highlighted by many researchers as an important aspect that deserves attention (Adnan et al., 2018). Alongside the body of literature reviewed by Keszey (2020), Rödel et al. (2014) conducted a study presenting respondents with driving scenarios with different degrees of vehicle autonomy. They found that a car's level of autonomy has an impact on user acceptance and experience. Despite these studies, some argue that knowledge about the public acceptance of autonomous driving is still limited, and more research is required to understand the psychological determinants of user acceptance (Buckley et al., 2018; Nastjuk et al., 2020; Xu et al., 2018).

A variable not extensively covered by prior AV research concerns algorithm aversion, the tendency for people to more rapidly lose faith in an erring decision-making algorithm than in humans, making comparable errors (Dietvorst et al., 2015). Shariff et al., (2017) feature this variable as one of the psychological challenges that stand in the way of widespread adoption of AVs, especially in the face of inevitable accidents that may and have already occurred. Along with the psychological phenomenon of illusory superiority, Shariff et al. (2021) investigated people's algorithm aversion to ride in an AV or with a taxi driver at different safety thresholds. This recent research by Shariff et al. (2021) spearheads the empirical examination of algorithm aversion in the context of AVs by investigating at least one related dimension (safety). However, AV safety might not be the only related dimension accounting for people's algorithm aversion. Indeed, autonomous ethics dilemmas have also arisen from how AVs will operate in cases of potential harm to passengers or pedestrians (Shariff et al., 2017). According to the Moral Machine Experiment, Latin American countries are cleanly separated in their own sub-cluster and show the highest level of preference for action in moral decision-making (Awad et al., 2018). The ethical dimension associated with AV algorithm aversion has thus far not been investigated. The present study aims to fill this research gap and proposes algorithm aversion as a deterrent of AV adoption from the perspective of (i) ethical judgment and behavior and (ii) emergency evaluation and performance. Moreover, our empirical investigation incorporates different autonomy levels as triggers of algorithmic aversion. Finally, we measure the impact of the latter construct on behavioral intention to use and how perceived hedonism mediates this effect. Overall, our research aims to answer the following research questions about AV perceptions and adoption: Does algorithm aversion toward AVs increase with higher automation? What is the impact of algorithm aversion on the behavioral intention to use an AV? Can perceived hedonism mediate the effect of algorithm aversion on the behavioral intention to use AVs?

Our research contributes to Information Systems (IS) and AV research by linking perceived hedonism with algorithm aversion, a construct that started attracting attention in the field only recently. This research sheds light on the interplay of the latter variables when framing potential users with different autonomy levels and accidents with different degrees of severity. Moreover, by conducting experimentation in Colombia in Latin America (N=400), we compensate for the regional imbalance in IS and AV research, which is mostly conducted in developed countries. From a theoretical point of view, our main contribution proposes that despite the blather around the Moral Machine Experiment and the controversy surrounding the moral deliberation of AV use, people's predisposition to use an AV is not hindered by algorithm aversion. Moreover, the user's intention to use an AV is enhanced through perceived hedonism, even when a higher level of algorithm aversion results from framing participants with a higher level of autonomy. On a practical level, our results suggest that algorithm aversion related to the ethical judgment and behavior of AV users need not be the focus for policy makers and AV manufacturers to foster AV adoption.

2. Conceptual framework and hypotheses development

2.1. Moral psychology of autonomous vehicles

One of the potential benefits of AVs is the reduction of traffic accidents caused by human error (Bonnefon et al., 2016). Indeed, since October 2018, Tesla has shared statistics that show the benefits of Autopilot – the feature included in all new Tesla vehicles that enables them to steer, accelerate and brake automatically (albeit requiring active driver supervision) within the car's lane. In its latest quarterly Vehicle Safety Report, Tesla claims to have registered one accident for every 4.19 million miles driven in which drivers had Autopilot engaged and contrasts this with the National Highway Traffic Safety Administration's (NHTSA) most recent data showing that in the United States there is an automobile crash every 484,000 miles driven. In the same report, the company recognizes that no car can prevent all accidents (Tesla, 2021).

Indeed, some cases might present imminent situations that will require AVs to make difficult ethical decisions where harm is unavoidable (i.e., saving pedestrians, car passengers or other traffic participants) (Bonnefon et al., 2016). In these cases, AVs should be tasked with distributing the harm they cannot eliminate: "*distribution of harm inevitably creates tradeoffs, whose resolution falls in the moral domain*" (Awad et al., 2018, p. 59). Indeed, such tradeoffs, or moral dilemmas, entail assigning relative value to different lives (Gill, 2020): "*robot cars will [also] need to have crash-optimization strategies that are thoughtful about ethics*" (Lin, 2016, p. 81).

The strong moral implications about how machines make decisions have received increasing attention from the research sphere as well as the media. Machine ethics or machine morality has thus emerged as an entirely new field dedicated to the study of moral decisions of autonomous agents (Gill, 2020). Researchers in the field agree with the need to guide and align machine behavior with the interests, expectations and values of all interacting parties (Awad et al., 2018). In a quest to address the major challenge of quantifying societal expectations and open the global conversation about the ethical principles that should guide AV behavior, Awad et al. (2018) conducted the Moral Machine experiment, which we detail in the following section.

2.2. The moral machine

The Moral Machine experiment (MME) is "*an online experimental platform designed to explore the moral dilemmas in the context of unavoidable fatalities faced by autonomous vehicles*" (Awad et al., 2018, p. 59). Each dilemma scenario shows two possible outcomes, contingent on a vehicle's action or inaction (swerving or staying on course), for which participants are asked to choose the outcome they prefer. The outcomes of the scenarios concern either the number of lives saved, the types of targets (i.e., young vs. old pedestrians, humans vs. animals).

The MME is considered by some misguided since there are relevant variants of trolley to which the project's participants are not exposed (Furey & Hill, 2020). Bigman and Gray (2020) criticize the MME for excluding equal treatment of human lives as an option presented to participants. Despite these opinions, Bigman and Gray (2020) recognize the revealed preferences in the MME: save more people over fewer and kill by inaction over action are consistent with results documented in previous research (Kallioinen et al., 2019 for references evidencing these discrepancies). This adjacent social dilemma was captured by Bonnefon et al. (2016), who found that people approve of utilitarian AVs (AVs that sacrifice car passengers for the greater good) and would like others to buy them. However, they would prefer to ride in self-protective AVs (AVs that are programmed to favor passenger safety and protect their passengers at all costs). Gill (2020) delved into this moral tension between self-preservation (protecting self) and pro-sociality (protecting the other) through a systematic examination of a one-to-one dilemma. The results from this research show a shift in moral judgments when the decision agent is an AV versus consumers themselves. For an AV not responsible for the outcome, participants considered harm to a pedestrian more permissible.

The integrating aspects of the MIT's MME (Awad et al., 2018) could help researchers understand AV acceptance from a social and ethical perspective (Meyer-Waarden & Cloarec, 2022). Along these lines, we consider the decisional functioning of AVs as a relevant topic of study that has practical implications that could break down consumers' psychological barriers and influence decisions to adopt (Gill, 2020; Kallioinen et al., 2019). We thus deem that the algorithms behind AVs (and consumers' acceptance or aversion toward them) are a key element that can influence the adoption of this technology.

2.3. Algorithm aversion

Algorithms are "*a set of steps that a computer can follow to perform a task*" (Castelo et al., 2019, p. 809). The rise of big data has led to an increased usage of algorithms in multiple domains to perform tasks in the place of humans for more accurate outcomes (Logg et al., 2019) or to delegate decision making to automated processes. In many decision domains, algorithms already outperform humans (Dietvorst & Bharti, 2019) in an increasing number of tasks, including driving cars.

Algorithms can be thought about in a number of ways, given their sociotechnical nature (Kitchin, 2017). As such, several studies have examined people's reactions, perceptions and attitudes toward algorithms in different settings. Despite the potential of better performance or generating enhanced outcomes, the predominant results indicate that consumers are averse to relying on algorithms to perform tasks that are typically done by humans (Castelo et al. 2019). For instance, Dietvorst et al. (2015) found that people lose confidence more quickly in algorithmic forecasters than human forecasters after seeing that they make the same mistake. This phenomenon is referred to as algorithm aversion, which refers to "*rejecting models in favor of their own (mis)judgments even when given evidence of the superior performance of models*" (Petropoulos et al., 2016, p. 851). However, it was found that reliance on automated advice systems increases when they can demonstrate their ability to learn, which can dilute algorithm aversion (Berger et al., 2021).

Another countermeasure for algorithm aversion is giving people some control over an imperfect forecasting algorithm by letting them modify it (Dietvorst et al. 2018).

It has been proposed that in decision domains where uncertainty is inherent, people may be unwilling to use even the best possible algorithm (Dietvorst & Bharti, 2020). Likewise, trust and reliance on algorithms seem to be even lower for tasks perceived as subjective versus objective, primarily because of a belief that algorithms are ineffective at subjective tasks (Castelo et al., 2019). Another important factor is overconfidence, a mindset where individuals treat their judgment as superior to that of other people (Logg et al., 2019). The latter is of special interest for the current research since overconfidence in one's own performance is famously prevalent in driving (Shariff et al., 2017). Overall, people seem to be averse to machines making moral decisions when human lives hang in the balance, even when the outcomes of these machines are positive (Bigman & Gray, 2018). For AVs, algorithm aversion may compound the reactions and fear of the public toward crashes involving such vehicles, which could deter consumers' adoption of AVs (Shariff et al. 2017). Driving is not only an uncertain and subjective task but also involves high stakes. We thus expect to observe algorithm aversion for AVs and that it has a negative impact on users' behavioral intention to use. Thus:

H1: Algorithm aversion has a negative effect on behavioral intention to use AVs.

2.4. *Level of autonomy*

The Society of Automotive Engineers developed a reference indicator for the level of autonomous driving. These indicators vary to the extent to which a car is taken over by autonomous systems and thus go from fully manual where the driving task is performed by the human driver (level 0) to full automation (level 5) (Bansal et al., 2016). At level 5, all driving tasks under all roadway and environmental conditions are fully performed by an AV technology system. In this category, the human occupants of a vehicle can be just passengers and need never be involved in driving (Panagiotopoulos & Dimitrakopoulos, 2018).

Multiple surveys have been conducted to deduce public opinion of AVs where different automation levels are compared (Bansal et al., 2016, Panagiotopoulos & Dimitrakopoulos, 2018) and gather important information from the public, such as interest, preferences and individual perceptions for different AV levels. The consequences of different automation levels have also been studied in the context of driver behavior. A driving simulator study where the drivers were requested to drive a part of a given track manually (but were then free to switch the mode from manual to semi or fully autonomous) showed that 55% of the route was driven in the fully automatic mode, which indicates that bus drivers prefer to use a fully autonomous vehicle in the context of their work (Brookhuis & de Waard, 2006).

To the best of our knowledge, the only study filling the void on how different autonomy levels impact the acceptance of AVs outside a work-related environment is that conducted by Rödel et al. (2014). Their research investigates user acceptance and user experience factors through different constructs from Davis' Technology Acceptance Model (TAM). The study concludes that user acceptance of AV differs significantly with regard to the degree of system autonomy. Specifically, attitudes and behavioral intention to use had the highest ratings for vehicles with level 1 autonomy and decreased gradually as the level of autonomy became higher. Likewise, trust was higher for level 1 and decreased with higher levels of autonomy. Thus, different levels of autonomy are closely related and have an impact on algorithm aversion. Thus:

H2: A higher AV automation positively impacts algorithm aversion.

2.5. *Beyond cognition: Incorporating affect in the intention to use AVs*

Algorithm aversion and the automation level of an AV can be considered essentially cognitive factors that can take part in the rational process of a person considering the use of an AV (Bettiga & Lamberti, 2017). This is in line with the TAM (Davis, 1989) and subsequent works (UTAUT; Venkatesh et al., 2012) that focused on purely cognitive factors to predict acceptance of technologies (Reinares-Lara et al., 2016). However, recent research has acknowledged a simultaneous interplay of cognitive and affective factors influencing individuals' attitudes toward technologies and behavioral intentions (Hohenberger et al., 2016; Liu et al., 2019b). In lieu of contrasting the cognitive and affective dimensions of the intention to adopt AVs, our research posits them at interplay, especially focusing on the role of perceived hedonism. Indeed, AVs offer both utilitarian and hedonic benefits, and intentions to use AVs have already proven to be correlated with affective reactions, such as pleasure and anxiety/perceived risk (Hohenberger et al., 2016; Zoellick et al., 2019).

2.6. *Algorithm aversion vs. Hedonism*

Risk or uncertainty affects users' confidence in their decisions (Im et al., 2008) and can determine purchase intentions and acceptance of technology (Brell et al., 2019). In a technological context, risk is defined as "*the likelihood of physical, social, and/or financial harm/detriment/loss as a consequence of a technology*" (Renn & Benighaus, 2013, p. 295). The importance of the risk is dependent on consumers' attitudes and aversion of negative consequences or on their perceptions of the degree of uncertainty.

It is argued that acceptance of technology is influenced by consumers' perception of risks and benefits (Brell et al., 2019). The literature on technology acceptance has investigated the impact of perceived risk at different levels of the adoption process. Perceived risk, associated with negative consequences in using technologies, decreases utilitarian value, attitudes, purchasing intentions and perceived hedonism (Im et al., 2008). Perceived hedonism is defined as "*the fun or pleasure derived from using a technology*" (Venkatesh et al., 2012, p. 161) or the degree to which a technology is perceived to be enjoyable (Nordhoff et al., 2020). Customers searching for hedonic value typically seek novel, varied, and complex sensational experiences, enjoyment or fun and are more willing to take risks (Keszey, 2020). A large body of research has found perceived hedonism to be an important driver of technology adoption (Chiu et al., 2014; Brown & Venkatesh, 2005; Childers et al., 2001). It was found that acceptance of Level 3 AV was influenced by hedonic motivation, although perceived risk decreased the users' behavioral intentions and hedonic value (Nordhoff et al., 2020; Meyer-Waarden & Cloarec, 2022; Keszey, 2020). The present research aligns with the widespread view that perceived risk triggers negative emotions, and autonomous driving is inherently related to risks (financial, physical, data privacy; Brell et al., 2019) which are expected to elicit affective responses (Hohenberger et al., 2016; Zoellick et al., 2019). We expect perceived risks, especially of a physical nature, to be captured through the construct of algorithm aversion, which will negatively impact perceived hedonism. Thus:

H3: Algorithm aversion has a negative effect on perceived hedonism.

Perceived hedonism, feelings of fun, pleasure, and other emotions should be experienced from driving an AV and act as a source of motivation (Meyer-Waarden & Cloarec, 2022). In line with the findings of Nordhoff et al. (2020), while investigating Level 3 automated vehicles, we expect perceived hedonism to be a predictor of behavioral intention to use AVs. Thus:

H4: Perceived hedonism has a positive effect on behavioral intention to use AVs.

2.7. *Controls*

Demographics, encompassing gender, age, and occupation, wield significant influence on individuals' psychological predispositions towards adopting autonomous vehicles (Meyer-Waarden & Cloarec, 2022). Gender disparities often manifest in varying levels of technological acceptance, with males typically exhibiting higher readiness for adoption. Age cohorts also play a pivotal role, with younger generations displaying greater openness to innovation compared to older counterparts. Additionally, occupation can shape attitudes, as those directly impacted by changes in transportation, such as professional drivers, may harbor reservations. Recognizing these demographic nuances is crucial for tailoring interventions and strategies to effectively address diverse concerns and motivations, thereby fostering widespread acceptance and utilization of autonomous vehicles.

When studying the intention to use autonomous vehicles, accounting for the gravity of accidents is essential (Shariff et al., 2017) as we suggest it might affect individuals' algorithm aversion tendencies and hedonistic considerations regarding the perceived enjoyment or convenience associated with using such vehicles.

Fig. 1 shows our conceptual model with the hypothesized relationships between level of autonomy, algorithm aversion, perceived hedonism and behavioral intention to use:

3. Method

3.1. *Experiment and measurement instruments*

The study employed a 2x2 factorial experiment, as depicted in Table 1, to investigate the impact of two key factors – autonomy level and accident severity – on participants' perceptions of autonomous vehicles (AVs). Each respondent was randomly assigned one of four scenarios, designed to prompt them to imagine either a level 2 or 5 AV, coupled with a low- or high-severity accident. This experimental design aimed to capture nuanced insights into individuals' attitudes and preferences regarding AVs across varying levels of autonomy and accident gravity.

We used scales from previous literature to assess the key constructs. Algorithm aversion was measured using the scale developed by Dietvorst et al. (2015), perceived hedonism was assessed using the scale by Sweeney and Soutar (2001), and behavioral intention to use was gauged using the scale developed by Venkatesh et al. (2012). All items were rated on seven-point Likert scales.

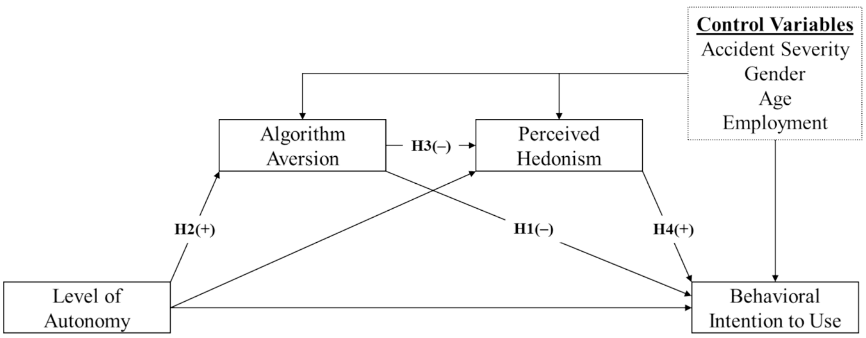

Fig. 1. Research model.

Table 1
2x2 factorial experiment scenarios presented in survey.

	Low severity accident	High severity accident
Low autonomy level	Imagine that you have a **level 2 AV** that will take you from point A to point B. You can assign some of the driving to your vehicle (speed management, safety distance management, wheel steering, etc.) but your vehicle can summon you to make you perform a maneuver (change lanes, exit the motorway, etc.). Thus, driving is both human and autonomous. Your vehicle is conventionally equipped with a steering wheel, brake pedals and an automatic driving device. Recently, there was an accident involving an AV. **Fortunately, no one was injured**.	Imagine that you have a **level 2 AV** that will take you from point A to point B. You can assign some of the driving to your vehicle (speed management, safety distance management, wheel steering, etc.) but your vehicle can summon you to make you perform a maneuver (change lanes, exit the motorway, etc.). Thus, driving is both human and autonomous. Your vehicle is conventionally equipped with a steering wheel, brake pedals and an automatic driving device. Recently, there was a terrible accident involving an AV. **Unfortunately, a family with two children died**.
High autonomy level	Imagine that you have a **level 5 AV** that will take you from point A to point B. Your vehicle is capable of autonomously performing all the driving tasks usually managed by humans (management of speed, safety distance, wheel steering, lane change, etc..) in all driving conditions. Your vehicle will therefore not be equipped in a conventional manner and will not have a steering wheel or brake pedals, but only an automatic driving device allowing exclusively autonomous driving. Recently, there was an accident involving an AV. **Fortunately, no one was injured**.	Imagine that you have a **level 5 AV** that will take you from point A to point B. Your vehicle is capable of autonomously performing all the driving tasks usually managed by humans (management of speed, safety distance, wheel steering, lane change, etc..) in all driving conditions. Your vehicle will therefore not be equipped in a conventional manner and will not have a steering wheel or brake pedals, but only an automatic driving device allowing exclusively autonomous driving. Recently, there was a terrible accident involving an AV. **Unfortunately, a family with two children died**.

3.2. Assessment of the measurement model

The measurement model assessment shows an excellent fit, with a chi-square test statistic of 13.204, 24 degrees of freedom, and a p-value of 0.96, indicating no significant difference between observed and predicted covariances. The SRMR value of 0.012 further confirms the model's robustness, well within the acceptable threshold.

3.3. Quality of the measurement instruments

To test for the reliability and validity of the measurement instruments, we conducted a confirmatory factor analysis. The psychometric properties for reliability of the scales were satisfactory, according to the literature standards. We assessed the reliability (Cronbach's α were greater than the 0.7 threshold) and the convergent validity (AVE above 0.50; see Table 2). The HTMT coefficients are lower than 0.85 (Henseler et al., 2015), signaling discriminant validity (see Table 3).

3.4. Common method variance

We established that common method variance was not an issue for the study (Podsakoff et al., 2003). The author used the ConMET package (De Schutter, 2021) to test the competitive models where items from two constructs load on the same latent variable. All the configurations significantly decreased the fit of the measurement model (i.e., χ^2 significantly increases with $p < 0.001$), as shown in Table 4. In addition, the authors tested the performance of Harman's one factor (Harman, 1967), and the results indicated that it performed poorly compared to the measurement model ($p < 0.001$).

3.5. Method of analysis

In mediation analysis, the PROCESS macro is a tool developed by Hayes (2021), a widely used method for assessing the indirect effect of an independent variable on a dependent variable through a mediator variable. This macro is typically used in statistical

Table 2
Reliability and convergent validity.

Constructs	α	AVE	Loadings
Algorithm aversion	0.75	0.51	
AA1: How confident are you in the ethical judgment/behavior of the AV algorithm?			0.73
AA2: How likely is it that the AV algorithm will correctly assess an emergency situation?			0.74
AA3: How do you think the algorithm will perform in the event of an accident compared to you?			0.68
Perceived hedonism	0.86	0.67	
PH1: Driving an AV would give me pleasure.			0.85
PH2: Driving an AV would be fun.			0.80
PH3: Driving an AV would be a pleasant distraction.			0.80
Behavioral intention to use	0.94	0.83	
BIU1: Looking at its advantages, I intend to buy an AV.			0.93
BIU2: Looking at its benefits, if I have access to an AV, I intend to buy one.			0.94
BIU 3: The likelihood that I will buy an AV is…			0.87

AA: algorithm aversion, PH: perceived hedonism, BIU: behavioral intention to use.

Table 3
Descriptive statistics and HTMT coefficients.

	M	SD	AA	PH	BIU
AA	4.87	1.16	–		
PH	4.80	1.45	0.57	–	
BIU	4.65	1.53	0.75	0.67	–

AA: algorithm aversion, PH: perceived hedonism, BIU: behavioral intention to use.

Table 4
Common method variance.

	$\chi 2$	df	χ^2/df	$\Delta\chi 2$
Proposed model	13.204	24	0.55	
PH and AA	226.311	26	8.704	213.107***
PH and BIU	301.881	26	11.611	288.677***
AA and BIU	114.324	26	4.397	101.119***
Harman's one factor	398.144	27	14.746	384.939***

Notes. ***$p < 0.001$, AA: algorithm aversion, Level: level of autonomy, PH: perceived hedonism, BIU: behavioral intention to use.

software packages such as SPSS, SAS, or R. The PROCESS macro allows researchers to estimate various mediation models, including simple mediation, parallel multiple mediation, and serial multiple mediation. It provides estimates of direct, indirect, and total effects, along with their associated confidence intervals and significance tests. The basic syntax for using the PROCESS macro typically involves specifying the variables for the independent variable, mediator variable(s), dependent variable, and any covariates, as well as specifying the model type and any additional options.

4. Results

4.1. Sample characteristics

The survey was conducted online in Colombia and distributed via social media (i.e., Facebook). Initially, 1214 respondents commenced the survey, with 418 (34.4%) completing it. After excluding 18 respondents who did not respond to all items regarding our focal constructs and demographics, our final sample comprised 400 participants. The average age of respondents was 27.08 years (SD=11.92), compared to 30.4 years in the Colombian population (Statista, 2024). Women constituted 52.8% of our sample, aligning closely with the gender distribution in the Colombian population (50.7%) (Statista, 2023). Additionally, the majority of respondents (60.5%) were employed, mirroring the employment rate in Colombia (55.3%) (Trading Economics, 2024). Although our sample was convenience-based, it exhibited notable comparability with the Colombian population, suggesting a reasonable level of representativeness.

4.2. Manipulation checks

To assess the manipulation of levels of autonomy and accident severity, we employed specific measures. Participants' perceptions of autonomy were gauged with the following item, "*Please rate the extent to which you perceive the autonomous vehicle in the scenario as capable of performing all driving tasks independently, on a scale from 1 (not at all capable) to 7 (extremely capable)*", and a Welch *t*-test revealed a significant difference ($t_{(398)} = -5.26$, $p < 0.001$) in perceived autonomy between Level 2 ($M_{\text{Level2}} = 4.16$, SD=1.60) and Level 5 ($M_{\text{Level5}} = 5.08$, SD=1.89). Similarly, accident severity was measured using the following item, "*Indicate your perception of the severity of the accident described in the scenario, considering its potential consequences, on a scale from 1 (not severe at all) to 7 (extremely*

Table 5
Estimation of the research model.

	Algorithm Aversion	Perceived Hedonism	Behavioral Intention to Use
Focal variables			
Level	0.32** (H2)	-0.22^{ns}	-0.19^{ns}
Algorithm Aversion		–0.57*** (H3)	–0.58*** (H1)
Perceived Hedonism			0.42*** (H4)
Control variables			
Accident Severity	0.23*	-0.07^{ns}	0.00^{ns}
Gender	0.18^{ns}	0.21^{ns}	-0.05^{ns}
Age	-0.00^{ns}	-0.00^{ns}	0.00^{ns}
Employment	-0.17^{ns}	-0.16^{ns}	-0.05^{ns}
R^2	0.04	0.23	0.53

Notes. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, ns: non-significant.

severe)", and another Welch *t*-test showed a significant difference ($t_{(364)} = –16.10$, $p < 0.001$) between the low accident severity (M=3.62, SD=1.92) and high accident severity conditions (M=6.28, SD=1.32). Thus, we validated the experimental conditions.

4.3. Test of the relationships

The findings presented in Table 5 and Fig. 2 demonstrate that algorithm aversion significantly diminishes ($b = –0.58$, $p < 0.001$) behavioral intention to use, thereby corroborating H1. Consistent with H2, the level of autonomy exhibits a positive and significant influence ($b = 0.32$, $p < 0.01$) on algorithm aversion. Moreover, the results align with H3, indicating that algorithm aversion significantly reduces ($b = –0.57$, $p < 0.001$) perceived hedonism. Lastly, H4 finds support as perceived hedonism positively and significantly impacts ($b = 0.42$, $p < 0.001$) behavioral intention to use.

Concerning the control variables, the outcomes reveal that demographics (i.e., gender, age, and employment) do not exert a significant effect ($p > 0.05$) on algorithm aversion, perceived hedonism, or behavioral intention to use. However, accident severity significantly enhances ($b = 0.23$, $p < 0.05$) algorithm aversion, although it does not significantly influence ($p > 0.05$) perceived hedonism or behavioral intention to use. Overall, the model explains 53% of the variance of behavioral intention to use.

4.4. Mediation analysis

We conducted a mediation analysis (Table 6) employing 5,000 bootstrap samples (Hayes, 2021). The total indirect effect from autonomy level to behavioral intention to use was found to be significant and negative ($b = –0.36$, $p < 0.05$, 95% CI=[–0.5729, –0.1406]). Specifically, two distinct indirect effects were observed, both significant with a 95% confidence interval, demonstrating a notably higher impact on behavioral intention to use. Firstly, the indirect effect through algorithm aversion, originating from autonomy level and leading to behavioral intention to use, was negative and significant ($b = –0.36$, $p < 0.05$, 95% CI=[–0.3341, –0.0527]). Secondly, the indirect effect via both algorithm aversion and perceived hedonism was also negative and significant ($b = –0.08$, $p < 0.05$, 95% CI=[–0.1445, –0.0206]). However, the sole indirect effect through perceived hedonism was not significant ($b = –0.09$, $p > 0.05$, 95% CI=[–0.2096, 0.0184]).

5. Discussion

5.1. Theoretical contributions

Our research findings align with previous but fragmented studies on the factors influencing the intention to use autonomous vehicles (AVs). Consistent with the findings of Liu et al. (2019b), our study indicates that AV adoption can be elucidated by cognitive factors, such as algorithm aversion, as well as affective factors like perceived hedonism. These factors interact within the cognitive processes and behavioral intentions of AV users. Similar to the evaluation of other disruptive technologies, users appear to employ both rational and emotional judgments (Bettiga & Lamberti, 2017) when assessing the utilitarian benefits of a technology. We demonstrate the interplay between algorithm aversion, as a cognitive factor, and the affective state or attitude stemming from perceived hedonism (Casaló et al., 2017). Our contribution to AV research lies in connecting ethical judgment and the intention to use AVs with the concept of algorithm aversion, which, to the best of our knowledge, has not been previously investigated.

5.1.1. Algorithm aversion

Our research confirms that higher automation leads to increased algorithm aversion and negatively affects users' perception of an autonomous vehicle's ability to handle emergency situations (Rödel et al., 2014). Specifically, compared to level 2 autonomous vehicles, level 5 conditions trigger greater algorithm aversion in emergency assessment but not in trust in the algorithm's ethical judgment or its performance compared to human drivers in accidents.

Users' tendency to doubt a level 5 autonomous vehicle's ability to assess emergencies optimally may be influenced by psychological mechanisms such as risk heuristics and illusory superiority (Shariff et al., 2017, 2021). Our results suggest that these mechanisms may

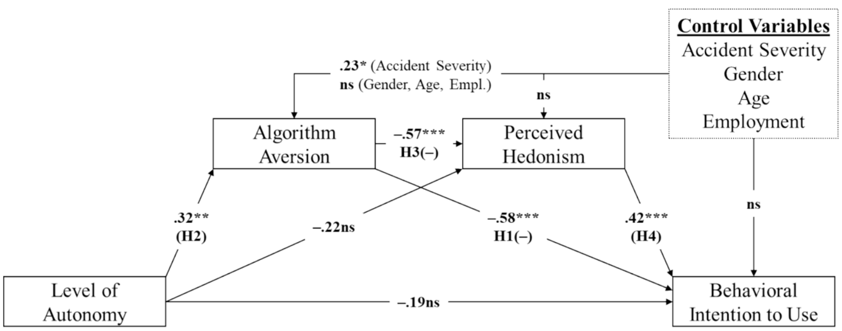

Fig. 2. Path diagram of the research model *Notes.* ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, ns: non-significant.

Table 6
Results of the mediation analysis.

Indirect effects	b	95% CI	
		Lower	Upper
Total	–0.36*	–0.5729	–0.1406
Level → AA → BIU	–0.19*	–0.3341	–0.0527
Level → PH → BIU	-0.09^{ns}	–0.2096	0.0184
Level → AA → PH → BIU	–0.08*	–0.1445	–0.0206

AA: algorithm aversion, Level: level of autonomy, PH: perceived hedonism, BIU: behavioral intention to use.

precede or moderate algorithm aversion. Availability heuristics may have made participants perceive higher risks due to recent accidents involving autonomous vehicles, contributing to doubts about their emergency assessment abilities. Illusory superiority was evident in participants' marginal belief that algorithms could outperform them in accidents, consistent with the tendency for individuals to overestimate their driving skills (Svenson, 1981; Roy & Liersch, 2013). These biases may explain why higher levels of automation trigger specific aspects of algorithm aversion.

Our research also confirms that algorithm aversion can discourage people from adopting self-driving cars, consistent with prior findings (Rödel et al., 2014). As autonomy increases, behavioral intention to use autonomous vehicles decreases, likely due to increased algorithm aversion and reduced perceived control (Shariff et al., 2021). This aligns with studies showing that anxiety reduces willingness to use autonomous vehicles (Hohenberger et al., 2016; Zmud et al., 2016). Overall, our findings support the preference for human drivers over autonomous vehicles and reluctance toward machine decision-making in moral dilemmas (Bigman & Gray, 2020; Shariff et al., 2021).

5.1.2. Perceived hedonism

Our third research question investigated how AV-related perceived hedonism mediates between algorithm aversion and the intention to use autonomous vehicles (AVs). Our model revealed that algorithm aversion's perceived risks negatively impact perceived hedonism and behavioral intentions through trust, emergency assessment, and human vs. machine subdimensions (Im et al., 2008). This finding supports prior research indicating that less pleasure due to higher perceived risk toward AVs leads to reduced willingness to use them (Hohenberger et al., 2016). People's emotions directly influence their judgments regarding technology acceptance (Liu et al., 2019a).

Perceived hedonism played a stronger mediating role in confidence in the algorithm's ethical judgment, followed by the assessment of the algorithm's emergency handling capabilities. It also mediated the relationship concerning the algorithm's expected performance compared to a human driver in accidents.

Our results highlight perceived hedonism's significance in AV adoption and contribute by demonstrating its role as an independent variable in technology acceptance, which has not been explored in established theories like UTAUT2 (Venkatesh et al., 2012). The mediation effect we identified builds upon the premise that higher positive affect and lower negative affect toward a technology predict higher acceptance (Liu et al., 2019b). Algorithm aversion may reflect lower negative affect, impacting the enjoyment of driving an AV and ultimately reducing its acceptance.

Moreover, our study suggests that algorithm aversion, coupled with perceived hedonism as mediators, explains the negative impact of high autonomy levels on the intention to use AVs. Consistent with previous findings (Rödel et al., 2014), highly autonomous cars are less accepted compared to those with advanced driver assistance systems. As autonomy increases, user acceptance, trust, and intention to use AVs decrease.

5.2. Policy implications

Although cars with level 5 autonomy are not yet available to the general public, our research sheds light on algorithm aversion and perceived hedonism as crucial determinants of social acceptability and adoption of such vehicles. Our findings and recommendations regarding these variables provide policymakers, AV developers, and other advocates with relevant insights to better understand and address some of the psychological challenges that hinder the acceptance of AVs, particularly those with high levels of autonomy.

Regarding the cognitive aspect of algorithm aversion, we first recommend that managers of AV manufacturers and other advocates focus on the subdimensions related to emergency evaluation. While advocating for transparency and preparing the public for the inevitability of accidents (Shariff et al., 2017), we propose two main efforts to enhance consumers' confidence in the ability of AV algorithms to accurately assess emergency situations. This could improve the perception of AVs across all levels of automation but may be particularly advantageous for level 5 AVs. Firstly, we suggest emphasizing the distinction between level 5 AVs and vehicles with lower levels of automation, which still require human drivers to be highly engaged in most driving tasks. This approach should be implemented in the short term to correct misunderstandings and adjust expectations regarding AVs. Indeed, the indiscriminate use of terms like "self-driving cars" across different automation levels, particularly in consumer-facing resources like social networks and blogs, has been misleading and detrimental to AV adoption. Hence, we propose utilizing consumer education to recalibrate expectations and counteract the potentially exaggerated media coverage of AV-related incidents in recent years (Shariff et al., 2017).

Secondly, managers should address specific concerns related to emergency assessment and performance of AVs, such as collision avoidance. To achieve this, they could (i) proactively disseminate factual data and statistics, such as those available in Tesla's Vehicle

Safety Report (Tesla, 2021), and (ii) provide practical insights into how AVs would respond in emergencies or when critical systems fail (Zhang et al., 2019). We recommend that assertions regarding the accurate assessment and performance of AVs in emergencies be substantiated with illustrative data, aligning the emergency dimension linearly with a specific metric.

Primarily, AV safety reporting has concentrated on the reduction in the number of accidents per million miles driven when automation or safety features are engaged versus disengaged (Tesla, 2021). In 2018, Tesla reported that its Model 3 achieved the lowest probability of injury of any vehicle ever tested by NHTSA (Tesla, 2018). Similarly, AV manufacturers and vehicle safety agencies could utilize available data to raise awareness about the number of accidents avoided due to the accurate assessment and performance of AVs compared to human drivers or non-automated vehicles. Thus, discussions on the safety benefits of AVs could extend beyond lives saved and directly address consumers' doubts about the ability of AVs to evaluate and respond in emergencies. This proposed metric could enhance users' perceptions of risk and challenge their overconfidence in their driving abilities (illusory superiority). Both initiatives described above should be effectively communicated through various channels (e.g., traditional media and social networks).

Understanding AVs as moral decision-makers seems to require further development before definitive conclusions can be drawn. Opinions regarding the morality of AVs vary (e.g., individuals may acknowledge utilitarian vehicles as more ethical but prefer self-protective cars for themselves (Bonnefon et al., 2016) or remain incomplete (e.g., the Moral Machine Experiment by Awad et al. (2018) depicts preferences for saving lives under forced inequality conditions based on structural and personal features but fails to capture preferences under conditions of allowed equality (Bigman & Gray, 2020). While existing findings offer guidance, additional insights are necessary to provide more precise recommendations for decision-makers (e.g., policymakers, AV technology developers, and manufacturers). Currently, communicating algorithmic improvements, shifting the ethics discourse to focus on absolute rather than relative risk, and mobilizing consumer virtue signaling as moral agents (Shariff et al., 2017) may be the most accessible approaches to enhance people's evaluation and trust in AV algorithms as moral decision-makers.

Attending to the cognitive factors in our model could help alleviate anxieties toward AVs and indirectly enhance the affective aspect. However, taking actions in the design and implementation of AVs to enhance perceived hedonism is equally crucial. According to research (Meyer-Waarden & Cloarec, 2022), the hedonic benefits of AVs are over seven times more influential than their utilitarian benefits. Therefore, to evoke more positive emotional responses, AV communications should emphasize the enjoyment, sensation-seeking, fun, and pleasure derived from traveling in such vehicles. Managers could actively influence hedonic motivation through the interior design of vehicles, potentially increasing users' well-being while making the vehicle aesthetically pleasing (Meyer-Waarden & Cloarec, 2022). Additionally, AV manufacturers could vividly demonstrate and promote the hedonic benefits (alongside the limitations) of riding in AVs by allowing customers to experience the systems firsthand (e.g., by offering test rides) (Nordhoff et al., 2020).

5.3. Limitations and future research directions

While our study contributes insights to AV literature, it's limited by a small, Colombia-centric sample skewed towards young, urban, tech-interested individuals. Nonetheless, findings align with similar studies using nonrepresentative samples across countries. Future research should focus on cultural diversity and larger samples.

Using social media for data collection in this research has three main limitations. First, there is a self-selection bias, as participants who opted to respond may differ significantly from those who did not, potentially skewing the sample and limiting its representativeness. Second, the survey's reach is confined to individuals with internet access and active social media use, excluding certain demographics such as older adults, lower-income groups, or those in rural areas with limited connectivity.

Understanding AV user acceptance remains incomplete, necessitating further investigation into determinants (Buckley et al., 2018; Nastjuk et al., 2020; Xu et al., 2018). Continuity with past research on AV ethics and social aspects is essential (Awad et al., 2018, 2020). Exploring framing effects on risk perception and the influence of liability and regulations on acceptance are key areas for future study (Othman, 2021).

Incorporating real-life information, like investigations into Tesla's Autopilot, could illuminate attitudes toward AVs (Fedor & Waters, 2021). Enhancing models such as UTAUT2 with novel variables and using virtual reality for testing can provide deeper insights into user responses (Awad et al., 2020; Bauman et al., 2014; Gilbert et al., 1998).

Compliance with Ethical Standards.

- Disclosure of potential conflicts of interest: None
- Research involving Human Participants and/or Animals: Yes
- Informed consent: Yes

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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