Transportation Research Part A 189 (2024) 104224

Contents lists available at ScienceDirect

Transportation Research Part A

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

"Let the Driver off the Hook?" moral decisions of autonomous cars and their impact on consumer well-being

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A R T I C L E I N F O

Keywords:
Autonomous driving
Ethics
Moral decisions
Well-being
Neuroscience

A B S T R A C T

Equipped with sophisticated, AI-based driver assistance systems, passenger cars are becoming increasingly intelligent. It seems that in a matter of a few years, fully autonomous vehicles will operate without any driver intervention. In this context, researchers are addressing the question of how fully automated vehicles should make decisions in critical situations. Should they spare the driver, children jumping out into the road or elderly people standing on the sidewalk? Projects such as MIT's Moral Machine are investigating the preferences of people from different nations and cultures for ethical decision algorithms. Evaluations of these automated decisions and how the may impact consumer perception and well-being are still scarce. In our experimental study, participants experienced a simulator-based driving situation in a fully autonomous car, after which they were confronted with alternative scenarios requiring automated action by the car in a critical situation. We measured the emotional status and well-being of our test-persons (N=33) in those critical situations using facial expression recognition (FER), electroencephalography (EEG), and standardized questions. The results show that there are detectable differences between the scenarios with respect to emotions as well as subjective well-being and behavioral intentions in the test group's responses to the questionnaire. Regarding FER and EEG, no statistically significant differences could be shown due to the small subsample.

1. Introduction

The transportation industry is undergoing a profound transformation by harnessing the power of artificial intelligence (AI) through the development and deployment of autonomous vehicle (AV) technology. In a general context, AI can be defined as "an unnatural object or entity that possesses the ability and capacity to meet or exceed the requirements of the task it is assigned when considering cultural and demographic circumstances" (Kelly et al., 2023). In the field of AV technology, AI "refers to systems that display intelligent behavior by analyzing their environment and acting – with some degree of autonomy – to achieve specific goals" (Samoili et al., 2020). Deep learning systems comprising various types of neural networks are the most common AI- methodologies applied to autonomous driving (Chib & Singh, 2023; Grigorescu et al., 2020). While AV technology utilizes intelligent AI algorithms, its development and adoption are influenced by a growing public debate about the ethical basis for allowing self-driving cars on the road (Atakishiyev et al., 2021; Kriebitz et al., 2022).

In this context, AV and AI are both technologies that reduce human involvement, which might lead to miscalculations or biases (Etienne, 2022; Hengstler et al., 2016; Kriebitz & Lütge, 2020). Despite these potential problems, AV technologies are widely expected

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https://doi.org/10.1016/j.tra.2024.104224
Received 20 September 2023; Received in revised form 28 June 2024; Accepted 20 August 2024

to reduce crash rates and fatalities, and the benefits may not be distributed equally among traffic participants (Goodall, 2017). Some individuals or groups may face greater risks from AV decision algorithms than in manual driving situations (Etienne, 2022; Harris, 2020). Rather than deciding randomly by rolling a die (Feldle, 2017; Gentzel, 2020; Lin et al., 2017), a crash situation requires that the software assign values to various objects to determine which should be spared by the AV. In addition to differentiating between objects (walls, streetlamps, etc.) and human beings, the AV must evaluate a range of factors related to human traffic participants, such as number, age, and location, to determine whom to protect in emergencies.

This experimental study delves into the technological progress of AV technology (Orieno et al., 2024; Padmaja et al., 2023) and its societal acceptance (Herrenkind et al., 2019; Hőgye-Nagy et al., 2023), emphasizing the need to investigate the effects of ethical AV decision-making on public perception.

Our literature review reveals three pertinent research gaps in the field. First, we uncover a need for empirical research focused on the possible outcomes of affective perception influenced by AI-based moral decision scenarios. Second, there is a shortfall in studies that integrate both explicit and implicit measurement methods. Third, there is an absence of research connecting consumers' perceptions of AI-driven moral decision-making to their acceptance of autonomous vehicles.

Considering these three research gaps, we outline the following research questions:

> RQ1: Do alternative AI-based moral decision scenarios involving autonomous cars affect consumers' emotions, subjective well-being, and intention to use them?
> RQ2: If they do, what differences emerge based on the action outcomes?

Our experimental study contributes to the literature at the intersection of ethical decision-making, emotional response, and subjective well-being in the context of AV technology. Moreover, by adopting a within-subject design and using innovative neuroscience tools for implicit measurements, we seek to obtain deeper insights into participants' emotional states, circumventing the limitations of self-reported data by observing physiological responses and facial expressions. Finally, we explore how moral dilemmas encountered by individuals using AV technology influence their emotions, well-being, and willingness to use this technology.

The subsequent sections outline the theoretical foundation, experimental methodology, and analysis techniques employed in our study. Our findings illuminate how different AI-driven ethical decision-making scenarios impact consumer emotions, well-being, and usage intentions. We conclude by discussing the broader contribution and implications of our findings and the role of ethical decision-making in shaping user perceptions, outlining the limitations of our study, and suggesting directions for future research.

2. Theoretical background

We base our research on ethical decision-making theory (EDM; Schwartz, 2016), which encompasses descriptive theoretical frameworks as opposed to normative ones, helping to explain cognitive processes such as reasoning or intuition, and affective processes, such as emotions (Izard, 1977) and subjective well-being (Diener & Chan, 2011), processes functioning in the brain (Schwartz, 2016). This understanding is crucial for comprehending individuals' moral judgments and behaviors (Reynolds, 2006; Salvador & Folger, 2009). In the case of AV technology, this decision-making is handed over to an AI (Caro-Burnett & Kaneko, 2022). As AI decisions are based on algorithms, research has to focus on the perceptual (cognitive and affective) consequences for drivers and consumers (Rhim et al., 2021).

Existing empirical studies have focused on cognitive and reasoning aspects: Basic considerations go back to the so-called "trolley problem", a philosophical thought experiment in which a trolley drives on a collision course with five people. The trolley can be diverted onto another track, where it will kill one instead of five people (Geisslinger et al., 2021; Goodall, 2019; Keeling, 2020; Thomson, 1985; Wolkenstein, 2018). Variants of similar scenarios have been discussed for AI algorithms in autonomous cars (Nyholm & Smids, 2016).

Considerable attention was given to the Moral Machine experiment conducted over a 2-year time period by the Massachusetts Institute of Technology (MIT, Awad et al., 2018; Harris, 2020). Outlining an experimental online platform, the Moral Machine offers various scenarios similar to the trolley problem in the context of autonomous driving. Participants must choose, based on their own moral judgment, between letting the autonomous car drive straight ahead or swerve into the other lane. Decisions result in different outcomes, implying at least one person's or animal's death. The Moral Machine experiment collected close to 40 million answers across more than 230 countries. General and global results show a preference for saving more lives versus fewer, younger people versus elderly and humans versus animals (Awad et al., 2018). Three identified cultural clusters have been associated with different world regions. While Western cultures show greater preferences for inaction, Eastern cultures spare those who are lawful, and Southern cultures spare females and people with higher status (Awad et al., 2018).

However, there has been much of general criticism about the valuing approaches of ethical decisions related to AI and AV technology (Etienne, 2021). For instance, Harris (2020) claims that driverless vehicles should always risk themselves and their occupants rather than choose between different groups of innocent bystanders. Nevertheless, in the AI and algorithm-driven discussion about AV technology making autonomous decisions in critical situations, "object-information-value-decision"- logic remains dominant and gives rise to different research directions (Gogoll & Müller, 2017; Lin et al., 2017). Some researchers propose requirements such as representation of reality, technical feasibility, universality, social acceptance, explainability, and transparency in governing AI and algorithm implementation (Geisslinger et al., 2021). Consequently, most object-valuing experiments such as the Moral Machine experiment have focused on the cognitive perception, the reasoning and human preferences for decision scenarios, whereas studies investigating affective consumer perceptions within ethical decision-making scenarios are lacking (Rhim et al., 2021; Schwartz, 2016).

Moreover, studies investigating affective perception parameters (such as emotions, Izard, 1977, and subjective well-being, Diener

& Chan, 2011) mainly evaluate the general impacts of AV technology on acceptance and usage intention. Subjective well-being is defined as an individual's self-evaluation of his or her life in terms of both emotional reactions and cognitive judgments (Diener & Chan, 2011). This definition encompasses positive affect, e.g., experiencing pleasant emotions and moods; negative affect, e.g., experiencing unpleasant emotions and moods; and general life satisfaction, e.g., cognitive assessments of overall life satisfaction (Diener & Chan, 2011). In this regard, subjective well-being is a key concept of transformative consumer research (Davis et al., 2016; Mick et al., 2019) that seeks to address the real problems faced by consumers. Previous technology adoption research has shown that subjective well-being is strongly affected by consumers' technology choices and usage, particularly in the case of autonomous driving (Betrandias et al., 2021; Meyer-Waarden & Cloarec, 2022). Other research has focused on assessing affective factors, such as consumer emotions, in response to unexpected decisions made by autonomous vehicles. However, these dimensions of affective perception have not yet been included in studies on AI-based moral decision alternatives. Considering the critical role of the affective dimension in ethical decision-making theory (EDM, Rhim et al., 2021; Schwartz, 2016), we identify our first contribution gap: the need for empirical research focused on the possible outcomes of affective perception (such as emotions and consumer well-being) influenced by AI-based moral decision scenarios.

Given that AI-based moral decision scenarios in traffic can potentially result in harmful consequences for participants (Awad et al. 2018), the question of how to accurately measure affective perceptions is raised. Particularly in light of the sensitive nature of these scenarios, traditional explicit measures for capturing affective perceptions, such as self-report questionnaire-based methods, may be subject to bias due to respondents' tendency toward social desirability (Fisher, 1993; Podsakoff et al., 2003). Unlike explicit measures, implicit measures bypass the need for conscious self-reflection by consumers. Instead, they employ innovative neuroscience measurement methods, such as facial expression recognition (FER), electroencephalography (EEG), eye tracking (ET), galvanic skin response (GSR) and heart rate per minute (HRPM), to observe the nonconscious and frequently automatic factors that shape consumer perception judgments and behaviors (Wijk and Noldus, 2021). Researchers have specifically highlighted the necessity of using multidimensional measurement techniques, both explicit and implicit measures, in the realm of ethical decision-making (Dinh et al., 2012). However, less research has made use of multidimensional measures to investigate affective perceptions in the context of AV technology (Arakawa et al., 2019; Cassioli et al., 2023; Lukovics et al., 2023; Strauch et al., 2019). For example, Lukovics et al. (2023) used neuroscience measurement techniques (EEG and ET) to implicitly measure consumer emotional responses while experiencing a self-driving vehicle. Similarly, Arakawa et al. (2019) used EEG, ET and HRPM to investigate differences between three scenarios in a driving simulator: manual- driving, autonomous- driving, and system- failure scenarios. As implicit emotional responses to ethical scenarios have been addressed to a certain extent, we identify second contribution gap: in the analysis of affective perceptions regarding AI-driven moral scenarios, there is a notable shortfall in studies that integrate both explicit and implicit measurement methods.

Furthermore, as automated decision routines could have different impacts on drivers' minds, emotions, and well-being, they might influence consumers' willingness to use the technology as well. To this extent, increased transparency on consumers' perceptions of moral decisions executed by the AI of autonomous vehicles could serve as a valuable contribution to technology acceptance research on AI and autonomous vehicles in a broader sense. This provides the third identified contribution gap: the absence of a connection between consumers' perceptions of AI-driven moral decision-making and their acceptance of autonomous vehicles.

3. Research design

3.1. Multidimensional measurement

Our research approach employs multidimensional measurement techniques to comprehensively evaluate the research questions raised. In addition to explicitly querying, we implicitly measure the variables of interest. Therefore, combining classical quantitative evaluation with implicit neuroscience measurement methods is crucial. The inclusion of these different data sources should provide as comprehensive a picture as possible. Thus, within our triangulating study- setting (Hussein, 2018; Jick, 1979), we utilized three distinct methods to evaluate emotions.

First, EEG was used as one of the measurement methods. EEG measures brain activity through small, metal electrodes attached to the scalp. These electrodes detect the electrical charges produced by brain cells, which are recorded as a graph. Specifically, we measured frontal alpha asymmetry (FAA) while participants were confronted with the scenarios as an emotional indicator across all participants. Neuroscientific research suggests "that lateralized brain wave activity (i.e., resting-state frontal EEG asymmetry) reflects the tendency or predisposition of an individual to engage in certain types of emotional (positive versus negative) and/or motivational (appetitive versus avoidant) responses" (Smith et al., 2017, p. 99). As the comparative measurement of summed electrical activity of the brain depending on different stimuli is more accurate within one participant (Smith et al., 2017), we chose a within-subject design because it offers significant advantages in controlling for individual differences, thereby enhancing statistical power. Moreover, a within-subject design is particularly beneficial when sample sizes are small and when detecting subtle changes is crucial (Charness et al., 2012). Therefore, we presented every scenario to each participants to compare their brain activity among scenarios. The EEG data were collected with an Enobio 8 from Neuroelectrics. The experiment focused on prefrontal areas, specifically positions F3, F4, F7, F8, AF3, AF4, AF7, and AF8.

Second, we measured seven basic emotions using the FER software Affectiva AFFDEX (Kulke et al., 2020). To analyze facial expressions, we recorded participants using a Logitech webcam (C920E). FER works based on machine learning algorithms by analyzing facial landmarks in the face of test- persons, which are then translated into emotional states and other affective metrics (Egger et al., 2019; Küntzler et al., 2021; Wolf, 2015). While EEG offers detailed insights into the brain's electrical activity and can reveal patterns associated with various emotions, it primarily captures internal physiological responses. FER, on the other hand, allows researchers to analyze external manifestations of those emotional states through facial expressions (Gannouni et al., 2021; Matlovic et al., 2016). To implement FER, we developed an experimental setup in which, in the first step, an artificial zero point was created by showing a neutral black cross for five seconds. Afterward, we presented the respective scenarios to the participants. The subsequent scenario then led to increases or decreases in the emotion values. These differences formed the basis of our analyses.

Third, the participants had to answer an online questionnaire presented on screen after each scenario (see Appendix A). This self-report questionnaire contained a validated emotional measurement scale (Boyle, 1984, 1987; Izard, 1977; Izard, 1982) and questions to measure perceived subjective well-being (Diener & Chan, 2011; Meyer-Waarden & Cloarec, 2022; Venkatesh et al, 2012) and the behavioral intention to use an autonomous car (Venkatesh et al, 2012) depending on the presented scenarios. The participants completed questionnaires after each scenario, which were administered via the QuestionPro platform (www.questionpro.com).

The EEG and FER data were collected using iMotions 10, software for recording and analyzing human behavioral data. The entire test procedure, i.e., the presentation of the stimuli and questionnaires, was also implemented with iMotions 10.

3.2. Sample description

Our experiment included a total of 33 participants. The average age was 26.97 years (SD=9.1 years), ranging from a minimum of 19 years to a maximum of 51 years. The sample comprised 57.6 % females and 42.4 % males. All participants were from a university environment and were not remunerated for their participation. To account for potential sampling biases, we inquired about participants' parenthood status and their close relationships with older people, such as grandparents. Most participants reported not having children, but the majority indicated having older relatives in their immediate family.

3.3. Driving simulator setup

Our experimental study employed a Level 5 fully autonomous driving simulator. Simulator studies offer standardized scenarios and the inclusion of specific incidents, unlike real-world test drives (Dosovitskiy et al., 2017). We constructed the driving simulator for an immersive experience, featuring an authentic driver's seat on a sound-immersive platform and three curved monitors providing a 180° field of view, all housed within a darkened tent. We used the simulation software City Car Driving (Forward Development, 2019) for the study. We designed an eight-minute driving scenario, which was consistently applied to all participants to standardize the experience of automated driving. For enhanced realism, the simulation included both urban and freeway driving conditions, along with incidents of varying levels of criticality (Gangopadhyay et al., 2019).

3.4. Experimental scenario setup

After the simulation, participants were allocated to two distinct groups for the experimental scenarios. The facial expressions of 12 participants were analyzed via a webcam, while the other 21 participants were fitted with an EEG cap. We split the groups because EEG and FER instructions conflict, making simultaneous analysis of a single participant impractical. Whereas for FER, the participant sits

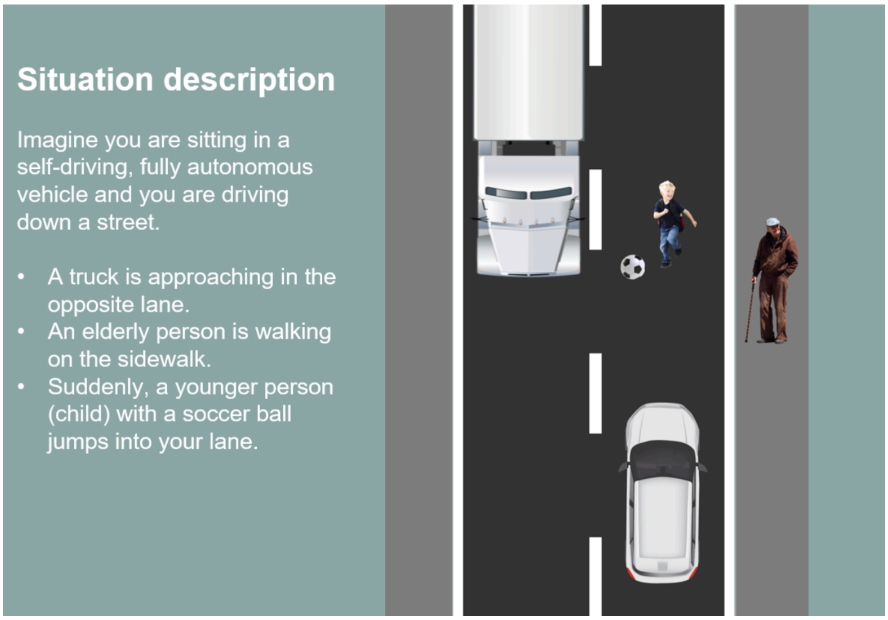

Fig. 1. Description of the initial situation presented to the participants.

naturally in front of the computer and has no restrictions regarding facial movements, for EEG the participant is instructed to remain completely still and not to move his or her head or face if possible. Furthermore, the EEG cap, secured under the chin, limits facial muscle movement.

Subsequently, participants in both groups followed the same procedure. The participants sat down in front of a computer. A baseline was determined at the beginning (45 sec). A black fixation cross was presented on a light gray background. The subjects were then given a description of the initial situation they were supposed to be in. The situation was described as follows (see Fig. 1): "Imagine you are sitting in a self-driving, fully autonomous vehicle and you are driving down a street. A truck is approaching in the opposite lane. An elderly person is walking on the sidewalk. Suddenly, a younger person (child) with a soccer ball jumps into your lane.".

After the initial description of the situation, the participants were confronted with possible decision-making scenarios in which the autonomous car could have reacted in various ways to a standardized critical traffic situation. To mitigate order effects in our within-subject design, we randomized the order in which the scenarios were presented, which each scenario preceded by a fixation cross. Considering the need to limit alternative stimuli in EEG studies to avoid participant fatigue or overwhelming the participant (Khushaba et al., 2013), we identified the variable Age as the most influential variable based on the Moral Machine experiment (Awad et al., 2018) to delineate the three fundamental scenarios as well as one neutral reference scenario (see Fig. 2).

In Scenario A, the autonomous vehicle swerves to the left and hits the truck driving in the opposite lane. The driver (participant) dies, and the younger person (child) and elderly person both survive.

In Scenario B, the autonomous vehicle swerves to the right and runs over the elderly person. The elderly person dies, and the younger person (child) and the driver (participant) survive.

In Scenario C, the autonomous vehicle fails to yield and runs over the younger person (child). The younger person (child) dies, and the elderly person and the driver (participant) survive.

Scenario D is a neutral reference scenario in which the autonomous car can stop without harming the people involved.

Following each scenario, participants completed an online questionnaire with validated questions on emotion, perceived subjective well-being, and behavioral intentions toward autonomous cars (Boyle, 1984, 1987; Izard, 1977, 1982), as well as questions on perceived subjective well-being (Diener & Chan, 2011; Meyer-Waarden & Cloarec, 2022) and the behavioral intention to use autonomous cars (Venkatesh et al, 2012). The exact procedure can be found in Fig. 3.

3.5. Data preparation

The main neuroscience research directions suggest "that lateralized brain wave activity (i.e., resting-state frontal EEG asymmetry) reflects the tendency or predisposition of an individual to engage in certain types of emotional (positive versus negative) and/or

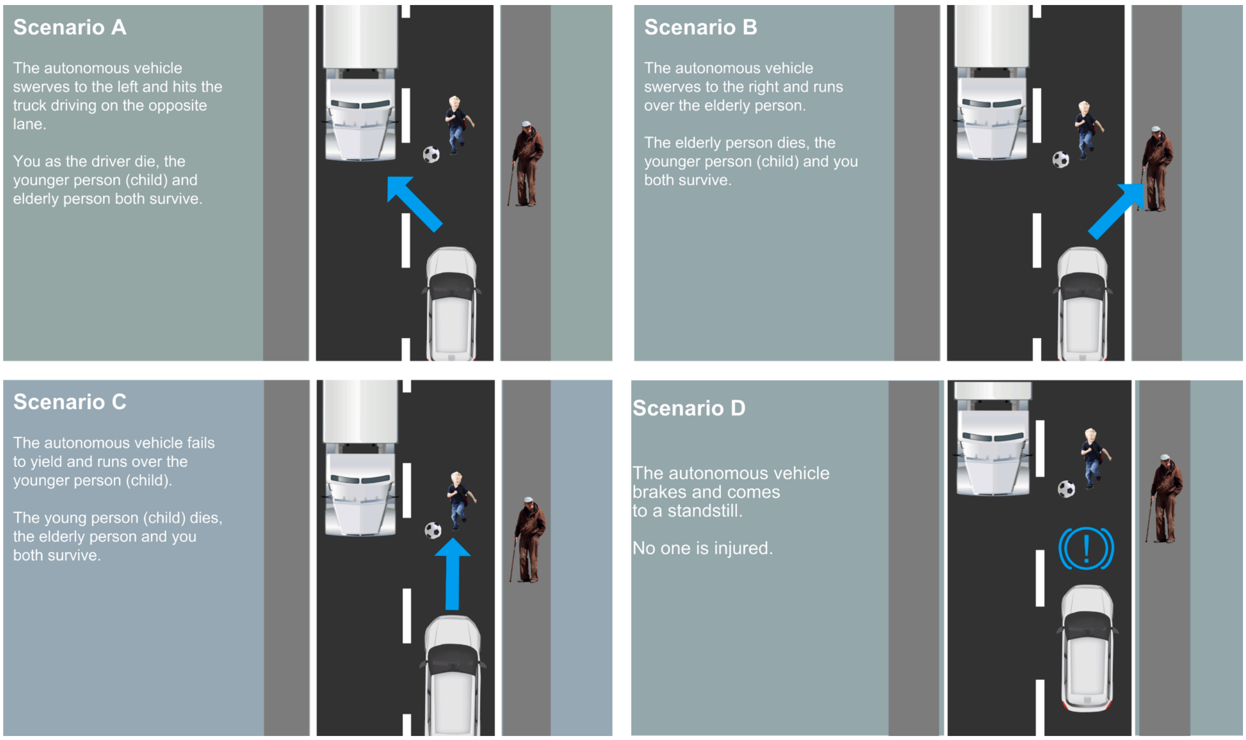

Fig. 2. Moral decision scenarios within the experimental setting.

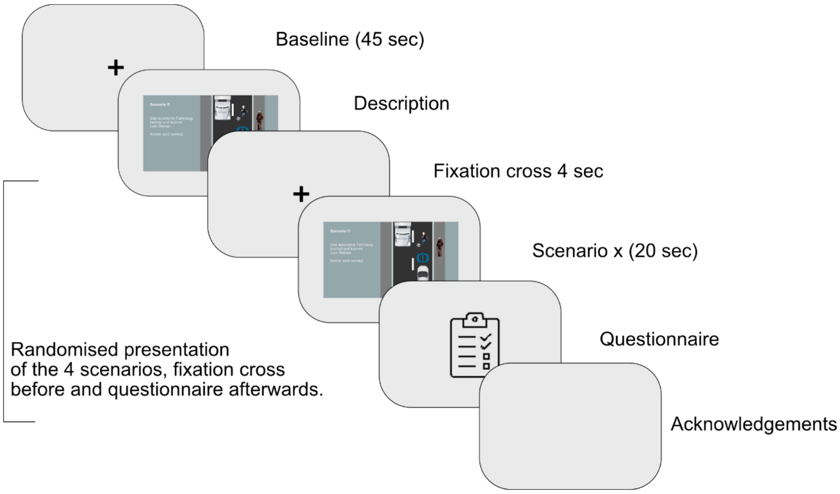

Fig. 3. Study procedure.

motivational (appetitive versus avoidant) responses" (Smith et al., 2017, p. 99). Given that comparative measurements of the brain's electrical activity in response to different stimuli are more precise on an individual basis (Smith et al., 2017), we chose a within-subject design. We presented every scenario to each participants to compare their brain activity among scenarios. We processed the raw EEG data for FAA analysis according to the methods outlined by Allen et al. (2004). Considering that the typical adult μV human EEG signal amplitude ranges from 10 to 100 μV, we classified any data above 120 as outliers. The power spectral density (PSD) was calculated using a Fast Fourier Transform (FFT), with a 1 s hamming window (5 s overlap). The frequencies selected for the alpha band were 8–12 Hz.

Following Briesemeister et al. (2013), the FAA was calculated as

$$\ln\left(Alpha_{Right}(AF4)\right) - \ln\left(Alpha_{Left}(AF3)\right)$$

This calculation was performed in the R notebook provided by iMotions. The difference between the mean FAA of the stimuli and the baseline was then determined to make the results of the participants comparable to each other. Those subjects who either had no results for the individual stimuli or no FAA value at the baseline due to a poor or no recorded signal were removed from the analysis. Eighteen of the original 21 participants were included in the analysis.

For the FER data, we first conducted postprocessing in iMotions to analyze the facial expressions frame by frame. Subsequently, we applied the "AFFDEX thresholding" algorithm within iMotions 10. Our analysis exclusively focused on thresholding the seven basic emotions. Following the software provider's recommendation, we set the threshold at 50 to indicate a moderately strong facial response (iMotions 10). The time percentages of each emotion were analyzed, i.e., the amount of time displaying one emotion out of the total time recorded for a stimulus.

4. Results

We analyzed the quantitative data using IBM SPSS Statistics 27. In the case of the questionnaire data (Q), the seven emotions as well as subjective well-being and behavioral intention represent the independent variables of interest measured by validated scales (see Appendix A). Table 1 shows the descriptive results of the mean values (Mean) with the respective standard deviation (SD) according to the four scenarios. The EEG data are based on values of frontal asymmetry, measured in μV. Table 2 shows the corresponding mean

Table 1
Descriptive statistics questionnaire and EEG data.

Variable	Source	N	Scenario A "driver"		Scenario B "elderly"		Scenario C "child"		Scenario D "neutral"	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD
Anger	Q	33	2.3939	1.3577	2.5455	1.2661	2.8283	1.4628	1.0909	0.2247
Contempt	Q	33	1.5859	0.8335	1.6212	0.8409	1.7475	0.9429	1.0404	0.1818
Disgust	Q	33	2.2626	1.2850	2.5152	1.2503	2.8788	1.3407	1.1111	0.2152
Fear	Q	33	2.7980	1.2609	2.9798	1.0831	3.1010	1.2869	1.5354	0.7815
Joy	Q	33	1.6061	0.8013	1.3131	0.5524	1.4040	0.6053	3.4444	1.0596
Sadness	Q	33	2.8384	1.2166	2.9091	1.2026	3.1313	1.3227	1.2929	0.5188
Surprise	Q	33	2.1313	0.8777	1.8586	0.7408	2.0808	0.8376	2.6162	1.1399
Subjective well-being	Q	33	2.3131	1.3095	2.7475	0.8720	2.3434	1.0443	4.6162	1.4292
Behavioral intention	Q	33	3.1717	1.5526	3.3939	1.0868	3.1515	1.1621	4.9697	1.5643

values and standard deviations.

The extent to which different emotions were detected by analyzing the faces of our participants is shown in percentages in Table 3. Several emotions can be visible in the face at the same time. A value of 0 % means that there are no signs of the corresponding emotion. A descriptive observation of the FER data shows only a few recognizable or detectable emotions. Therefore, the sample size N varies for each emotion measurement. Consequently, the software was unable to detect these emotional states in the faces of the participants during the experimental situation. The limited sample size restricts further statistical analysis or interpretation of the FER data.

To assess individual differences in our within-subject experimental setting, we employed a repeated- measures ANOVA to investigate the effects across four distinct scenarios. This approach enabled us to analyze the variance within subjects, providing insights into the consistency of their responses across different conditions. Before conducting the ANOVA, we performed preliminary checks to validate our data's suitability for this analysis. We utilized several tests, including Q-Q plots. Visual inspection suggested an approximately normal distribution. Moreover, our sample size exceeded 30 participants (N>30), a threshold that supports the assumption of normality in the sample distribution (Fischer, 2011). Thus, the combination of our preliminary data checks and the sufficiently large sample size laid a robust foundation for the application of repeated- measures ANOVA in our study. Since the literature recommends a correction even for a nonsignificant result of the Mauchly test for sphericity, we exclusively applied the Greenhouse-Geisser correction (Girden, 2003). We report Partial Eta2 to indicate the proportion of emotion variance attributable to the scenario, while Cohen's f was employed to gauge effect size within the analysis. According to Cohen (1992), the thresholds for effect size are delineated as follows: 1 for a small effect, 25 for a medium effect, and 4 for a large effect. Table 4 displays significant variances in all evaluated emotions as well as subjective well-being and behavioral intention across the scenarios. The FAA analysis revealed no significant scenario-based differences (see Table 5).

Given its robustness, we conducted Bonferroni post hoc tests to further explore significant differences between scenarios (Field & Iles, 2018). The p values presented in Table 6 primarily indicate variations between the neutral scenario and the remaining scenarios. Specifically, regarding disgust, a significant difference was observed between the"driver" Scenario A and the "child" Scenario B while the disparity between the "elderly" and "child" scenarios was marginally above the threshold of significance. Likewise, the significance of "Joy" and "Subjective well-being" slightly surpassed the threshold when comparing the "driver" and "elderly" scenarios. However, a significant difference persisted in subjective well-being between the "elderly" and "child" scenarios.

5. Discussion

The main objective of this study was to employ a triangulated approach to data collection. In addition to traditional questionnaires, we utilized implicit neuroscience measurement methods, namely, EEG and FER. These procedures enabled us to measure emotional status (both implicitly and explicitly) and subjective well-being. Participants experienced a simulator-based driving scenario in a fully autonomous car, followed by alternative ethical action scenarios in critical traffic situations.

Regarding the research questions raised, we can derive the following findings from the questionnaire data. In principle, a highly significant mean difference exists between the scenarios for each of the emotions surveyed. However, the corresponding post hoc test makes it clear that this significance is primarily due to the significantly lesser or greater emphasis on emotions in the case of neutral Scenario D, in which no one dies. Despite this, a descriptive analysis of the individual values reveals a clear pattern: For the obviously negatively connoted emotions Anger, Contempt, Disgust, Fear, and Sadness, the corresponding values are always highest in the case of the death of the child (Scenario C). The death of the elderly person (Scenario B) followed in second place and one's own death (Scenario A) was rated lowest in comparison with these emotions. It thus becomes clear that these negative feelings are perceived or pronounced more strongly in the case of the death of third persons than in one's own death. The corresponding values for the neutral Scenario D without death were, as expected, significantly lower. The pattern shown is consistent with existing research findings. We assume that conventional explicit, self-report-based questionnaire methods for measuring emotions may have biases due to participants' social desirability concerns (Fisher, 1993; Podsakoff et al., 2003).

Notably, all of the emotion averages are considerably lower for the emotions Contempt, Joy, and Surprise. This result seems understandable since these emotions, especially Joy, are unexpected due to the context. However, since FER can collect these emotions, they were consequently also included in the questionnaire. Despite the difficulty in transferring these feelings to the context, the corresponding response pattern is also evident here, namely that the death of a third party is of greater relevance than the death of oneself.

Interestingly, the pattern changes when measuring subjective well-being: the ordering of the child before the elderly person before oneself is altered. Subjective well-being is now lowest in the case of one's own death, followed by the death of the child, and that of the elderly person and is, as expected, highest when no one dies. This deviating pattern is surprising at first, as it would be expected to a certain extent that individual emotions should be reflected in their overall subjective well-being. However, it can be assumed that in the case of this more global variable, the effect of social desirability is less pronounced, and ultimately, one's own self is given the

Table 2
Descriptive statistics of the EEG data.

Variable	Source	N	Scenario A "driver"		Scenario B "elderly"		Scenario C "child"		Scenario D "neutral"	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD
FAA	EEG	18	−0.00425	0.2798	0.09763	0.2658	−0.00069	0.4307	−0.10038	0.4528

Table 3
Descriptive statistics for facial recognition.

Variable	Source	N	Scenario A “driver“		Scenario B “elderly“		Scenario C “child“		Scenario D “neutral“	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD
Anger	FER	1 out of 12	0 %	–	0 %	–	0 %	–	3.51 %	–
Contempt	FER	0 out of 12	0 %	–	0 %	–	0 %	–	0 %	–
Disgust	FER	0 out of 12	0 %	–	0 %	–	0 %	–	0 %	–
Fear	FER	1 out of 12	0 %	–	0 %	–	3.34 %	–	1.67 %	–
Joy	FER	2 out of 12	0 %	–	4.01 %	0.71	3.34 %	1.89	3.50 %	3.30
Sadness	FER	1 out of 12	0 %	–	4.17 %	–	0 %	–	0 %	–
Surprise	FER	1 out of 12	0 %	–	0 %	–	2.50 %	–	0 %	–

The percentage of time for the display of an emotion on the participant’s face out of the total time recorded for a stimulus.

Table 4
Results of the repeated measures analysis of variance according to the four scenarios for the questionnaire data.

Variable	F value	DF1	DF2	p value	Par. Eta^2	Cohen f
Anger	26.148	3	96	0<.001	0.450	0.905
Contempt	10.757	3	96	0<.001	0.252	0.434
Disgust	29.276	3	96	0<.001	0.478	0.957
Fear	39.621	3	96	0<.001	0.553	1.112
Joy	76.632	3	96	0<.001	0.705	1.546
Sadness	52.362	3	96	0<.001	0.621	1.280
Surprise	7.173	3	96	0<.001	0.183	0.473
Subjective well-being	49.313	3	96	0<.001	0.606	1.240
Behavioral intention	31.641	3	96	0<.001	0.497	0.994

Table 5
Results of the repeated measures analysis of variance according to the four scenarios for the EEG data.

Variable	F value	DF1	DF2	p value	Par. Eta^2	Cohen f
FAA	1.358	3	45	0.268	–	–

Table 6
Results of the post hoc tests.

Differences	N	A vs. B	A vs. C	A vs. D	B vs. C	B vs. D	C vs. D
Anger	33	0.292	1.00	0<.001	1.00	0<.001	0<.001
Contempt	33	1.00	1.00	0.003	0.829	0<.001	0.001
Disgust	33	1.00	0.017	0<.001	0.085	0<.001	0<.001
Fear	33	1.00	0.473	0<.001	1.00	0<.001	0<.001
Joy	33	0.061	0.303	0<.001	1.00	0<.001	0<.001
Sadness	33	1.00	0.239	0<.001	0.301	0<.001	0<.001
Surprise	33	0.602	1.00	0.220	0.491	0<.001	0.029
Subjective well-being	33	0.090	1.00	0<.001	0.035	0<.001	0<.001
Behavioral intention	33	1.00	1.00	0<.001	0.252	0<.001	0<.001

The p-values for the comparison of the scenarios are shown. A means “driver“ Scenario A, B is “elderly“ Scenario B, C stands for “child“ Scenario C, and D is “neutral” Scenario D.

highest priority in such a critical situation (Chung & Monroe, 2003; Randall & Fernandes, 1991). Consequently, it would be understandable why the value for subjective well-being is comparatively lower in the case of one’s own death (Scenario A).

From a descriptive perspective, the respective mean values show that the behavioral intention to use an autonomous vehicle in everyday life tends to be rather restrained. This reserved attitude likely results from the negative, potentially fatal driving situations experienced. This interpretation also appears conclusive, as in the case of the neutral Scenario D, the intention to use AVs is significantly more positive than in moral dilemma scenarios A to C, in each of which there is one fatality.

Working with face recognition software certainly appears to be a valuable alternative to classic questionnaire design or at least a supporting component for emotion research. Unfortunately, our case does not show usable data for comparison. However, it can be assumed that the chosen static presentation method of the scenarios had a decisive effect. In the case of a video presentation, more usable emotion measurements might indeed result.

The third survey method via EEG did not show significant differences between the scenarios. However, the purely descriptive comparison of the FAA signals presented a thought-provoking picture. In the case of one’s own death, this value was more negative than in the case of the death of the child or the elderly person. This result is therefore comparable with the findings regarding the measurement of subjective well-being. In the case of implicit measurement, people are ultimately closest to themselves in such a critical situation of death. In the FAA data, it is also initially surprising that in the case of neutral Scenario D, when no one is harmed, the corresponding value is the most negative among all of the scenarios. However, this value might be explained by the graphical presentation of neutral Scenario D. The exclamation mark visualized here may have a negative disturbing influence on the participants at the first moment of viewing. Its presence may suggest to the viewer a certain degree of caution, which could explain the negative tendency of the value.

In conclusion, AI-based moral decision scenarios in autonomous cars significantly impact consumer emotions, subjective well-being, and usage intentions. Regarding the chosen experimental design, the classic self-report survey questions revealed interesting descriptive findings. A larger sample size could provide even more clarity in the case of both explicit and implicit measurements of emotions. An improvement of the experimental design, e.g., using the FER measurement while participants viewed moving, nonstatic images, could also adress the problem of biased results due to social desirability in explicit emotion measurement and thus provide additional implicit measurement results to the EEG. This approach would offer the opportunity to obtain a stronger focus and corresponding knowledge regarding implicitly measurable influencing factors.

6. Contributions

We provide several theoretical contributions to the field of AV technology, focusing on how AV moral decision-making affects consumers' emotional and cognitive responses. In summary, our research contributes to theory in the following ways.

First, our primary contribution lies in enriching ethical decision-making theory (EDM, Schwartz, 2016) for autonomous driving applications by focusing on the unexplored intersection of ethical decision-making scenarios, emotions, and subjective well-being. While prior research has investigated the ethical decision-making scenarios posed by AV technology (Caro-Burnett & Kaneko, 2022; Etienne, 2021; Rhim et al., 2021), there is a lack of studies that delve into how these moral dilemmas may impact the emotional states and perceived well-being of possible users of AV technology (Betrandias et al., 2021; Yokoi & Nakayachi, 2021). By incorporating an empirical, within-subject design (Charness et al., 2012), we investigate how participants affectively react to different ethical AV decision-making scenarios. By doing so, we provide meaningful insights into the perceived emotions and subjective well-being of participants in different scenarios. With this specific experimental design, we extend the literature not only by investigating the general affective perception of autonomous vehicles (e.g., Baccarella et al., 2021; Betrandias et al., 2021; Du et al., 2021; Huber et al., 2022; Meyer-Waarden & Cloarec, 2022), but also by capturing the nuances of individuals' perception dynamics depending on different ethical scenarios and by shedding light on how the decision-making of AV technology intersects individuals' affective responses in terms of emotions and subjective well-being. Given the profound role that emotions and subjective well-being play in shaping public acceptance and trust in new technologies (Beaudry and Pinsonneault, 2010), understanding the emotional and psychological impacts of different ethical decisions made by AV technology is crucial for their integration into society (Caro-Burnett & Kaneko, 2022). In this regard, our research strives to provide valuable insights into the development of AV technology that is not only ethically sound but also aligned with the emotional and well-being considerations of potential users, thereby fostering greater acceptance and integration of this technology into daily life.

Second, our study contributes to the rapidly developing research domain of neuroscience and implicit measurement techniques (Srivastava & Bag, 2024; Znanewitz et al., 2018) and how it can contribute to an improved understanding of ethical decision-making research. The prevailing body of research on ethical decision-making in the context of AV technology predominantly relies on explicit measurement methods, such as surveys and interviews, to evaluate individuals' affective perceptions. However, explicit and self-reported measurement methods are often subject to bias due to social desirability, limited self-awareness, or the inability to accurately articulate complex feelings (Fisher, 1993; Podsakoff et al., 2003), particularly in ethical decision-making research (Chung & Monroe, 2003; Randall & Fernandes, 1991). Recognizing this limitation, our study explores relatively uncharted territory by employing implicit neuroscience measurement techniques in the study of AV technology, specifically EEG and FER, to investigate the emotional underpinnings of ethical decision-making scenarios. These methods offer a more nuanced and immediate window into participants' affective states, bypassing the constraints of self-report measures by capturing physiological and facial expression indicators of emotional responses (Dinh et al., 2012; Wijk and Noldus, 2021). Thus, this research addresses a contribution gap by providing novel insights into the automatic, unfiltered emotional reactions elicited by ethical scenarios in autonomous driving. This methodological approach not only enriches our understanding of the complex interplay between ethics, emotion, and technology but also paves the way for the development of AV systems that should align with human ethical values and societal norms.

Third, we contribute to transformative consumer (Davis et al., 2016; Mick et al., 2019) and technology acceptance research on AVs and autonomous driving in general, as we investigate the potential behavioral intention to use AV technology and subsequent affective perception factors (such as consumer subjective well-being; Diener & Chan, 2011) depending on the different ethical scenarios presented. By doing so, our study addresses a broad research gap in understanding how moral dilemmas in autonomous driving influence perceived emotions, consumer subjective well-being and the subsequent behavioral intentions of potential users of such vehicles. While there has been extensive research on technology acceptance behavior toward AV technology (e.g., Bernhard et al., 2020; Herrenkind et al., 2019; Hőgye-Nagy et al., 2023) and the ethical decision-making implications of autonomous vehicles (Caro-Burnett & Kaneko, 2022; Etienne, 2021; Martinho et al., 2021; Rhim et al., 2021), there is a gap in interdisciplinary research that combines ethical decision-making scenarios and their impact on affective perceptions and on the behavioral intentions of potential users. Existing studies lack a simultaneous examination of how different ethical scenarios presented by AV technology might influence the emotions and consumer subjective well-being associated with autonomous vehicles and how these moral decisions affect an individual's willingness or reluctance to use AV technology. However, this oversight is noteworthy because the acceptance and widespread adoption of autonomous vehicles will depend not only on their technical proficiency and safety but also on how well they align with societal and emotional ethical standards and how these standards influence user behavior. Our research fills this gap by empirically examining the relationship between moral dilemmas presented in autonomous driving contexts and individuals' perceptions of emotions, consumers' subjective well-being and behavioral intentions to adopt AV technology. By incorporating both affective considerations and user behavior into the discourse, this study contributes to a more holistic understanding of the factors influencing the adoption of AV technology influenced by possible moral dilemma situations.

7. Limitations and research outlook

The consideration of different measurement methods for the recording of emotional states regarding relevant ethical decision-making scenarios represents a clear, distinctive feature of this experimental survey. Nevertheless, we identify limitations that will be discussed below.

The current sample consisted of relatively young participants from a university setting. It can be argued that samples from younger populations represent a future segment for the use of AV technology, as younger generations tend to be more enthusiastic about new technologies, products, and services (Classen et al., 2023; Huang et al., 2022; Meyer-Waarden & Cloarec, 2022). However, younger participants might value the life of a younger person (child) more highly than that of an older person in an AV moral dilemma due to a perceived similarity in age and life stage, leading to greater empathy and identification with individuals of their own age group (Awad et al., 2018). Therefore, further research should try to improve the sample composition in terms of age. Moreover, a balanced gender distribution is desirable, as in the present sample females are slightly overrepresented. Additionally, in retrospect, the robustness of our analysis could have been greatly augmented by employing a larger sample size to enhance the statistical power of our within-subject design analysis. We posit that the differences, which were descriptively notable, would likely achieve statistical significance in a larger sample. This would not only strengthen the validity of our findings but also provide a more compelling argument for the generalizability of our results.

From a technical perspective, the use of neuroscience measurement techniques is quite challenging. In the case of EEG, the quality of contact between the electrodes and the scalp is problematic, especially for people with long hair. In addition, the slightest movement of the participants during the data collection phase can influence the EEG data. Poor EEG contact quality and participants' movement, can significantly impact data quality and reliability. For instance, increased noise can obscure the underlying brain waves that are of interest, and artifact contamination can lead to unwanted signals not generated by brain activity that mimic or obscure genuine EEG signals, leading to misinterpretation (Fitzgibbon et al., 2007; Urigüen & Garcia-Zapirain, 2015). Despite appropriate requests to the participants, this effect often cannot be avoided and could also have affected our data analysis. Moreover, the comparability between the participants is challenging because every brain has a different latency, and therefore, quite different measured values can result. These aspects should always be considered when interpreting the data collected via such neuroscience measurement techniques.

Moreover, the different dilemma scenarios were only presented as static images with corresponding explanatory text about the situation after the test drive with the driving simulator. While static images are valuable for controlled comparisons, they lack the dynamism inherent to driving scenarios. Static images cannot fully capture the urgency or complexity of the ethical decision-making issues that drivers face in unexpected moral decision scenarios. Moving to a more dynamic simulation would address this issue by allowing participants to experience unfolding events, closely mimicking real-life situations (Newman et al., 2022; Samuel et al., 2020). Therefore, we assume that a more realistic visual experience in the driving simulator would have produced more meaningful results, especially in the case of EEG as well as FER measurements. For future research, a visual implementation of the dilemmas in the driving simulator is planned by using the open-source simulator software CARLA, which allows the manipulation of a wide range of variables in real- time, such as weather conditions, time of day, and unexpected pedestrian or vehicle behavior.

Despite these limitations, the triangulated approach of the present study provides a good first impression that different measurement methods have their own justification and can produce valuable measurement results. In summary, based on our findings and limitations, we suggest that subsequent studies take these limitations into account. Furthermore, in addition to sample composition in terms of age and gender, we recommend including the impact of cultural differences (e.g., as a moderating variable), as these might influence the perception of ethical decision-making in AV scenarios (Awad et al., 2018). Additionally, it is important to note that AV technology extends beyond personal vehicles. Therefore, it would also be interesting to examine conceivable autonomous modes of public transportation (e.g., autonomous shuttles) in ethical decision-making scenarios. It is possible that the outcomes of the respective scenarios would be assessed differently in that contextsince the emotional distance to the driving situation as a passenger is greater than when one is the driver in one's own car.

CRediT authorship contribution statement

Marc Kuhn: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization. **Vanessa Reit:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis, Data curation. **Maximilian Schwing:** Writing – review & editing, Visualization, Investigation. **Sarah Selinka:** Writing – review & editing, Writing – original draft, Investigation.

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.

Data availability

Data will be made available on request.

Appendix A:. Measurement items of self-reported questionnaire

Latent variable	Manifest variable	Source
	How do you feel? Please rate the following emotional states. (1 = not at all, 2 = slightly, 3 = moderately, 4 = considerably, 5 = very strongly)	Izard (1977)
Anger	enraged	
	angry	
	mad	
Contempt	contemptuous	
	scornful	
	disdainful	
Disgust	feeling of distaste	
	disgusted	
	feeling revulsion	
Fear	scared	
	fearful	
	afraid	
Joy	delighted	
	happy	
	joyful	
Sadness	downhearted	
	sad	
	discouraged	
Surprise	surprised	
	amazed	
	astonished	
Subjective well-being	Please rate the following statements.(1 = fully disagree, 2 = disagree, 3 = slightly disagree, 4 = neither agree nor disagree, 5 = slightly agree, 6 = agree, 7 = fully agree)	Diener and Chan (2011); Meyer-Waarden and Cloarec (2022)
	If I used this autonomous vehicle, my life quality would be improved to ideal.	
	If I used this autonomous vehicle, my well-being would improve.	
	If I used this autonomous vehicle, I would feel happier.	
Behavioral intention to use	Please rate the following statements.(1 = fully disagree, 2 = disagree, 3 = slightly disagree, 4 = neither agree nor disagree, 5 = slightly agree, 6 = agree, 7 = fully agree)	Venkatesh et al, 2012
	If I had access to this autonomous vehicle, I would try to use it in my daily life.	
	I would make regular use of this autonomous vehicle if it was available.	
	I intend to use autonomous vehicles in the future.	

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