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Combining survey-based and neuroscience measurements in customer acceptance of self-driving technology

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ABSTRACT

In recent years, the issue of consumer acceptance of self-driving cars has come to the forefront of interest among policymakers, researchers and automotive industry experts. Anchored in the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), these studies are typically based on survey data from respondents who have not used self-driving vehicles. The survey, being a perception-based measure has several limitations, such as social desirability bias, inaccuracy due to time pressure, just to name a few. In addition, the change in intention to use self-driving vehicles as a result of actual test use deserves more academic attention. To address this limitation, volunteers were invited to participate in a test drive as passengers in a self-driving vehicle, testing their acceptance of technology using an adapted version of UTAUT2 questionnaire before and after the ride. Neuroscience measurements were also performed: real-time electroencephalography (EEG) and eye-tracking were recorded during the ride. The explanatory power of our regression model was high (97%) using this combined research method. Our preliminary results suggest, that in a real-life test technology acceptance was related more to emotional experience during the ride and less to other elements of the UTAUT2 model – which challenges the results of previous methods based solely on surveys.

1. Introduction

Self-driving technologies are identified as radical innovations (EC, 2019), which will transform the daily lives and habits of people living in urban environments in the next decades, regardless of whether they are involved in transport as drivers, cyclists, pedestrians, or in any different roles (Cohen & Stilgoe et al., 2020). The importance of the topic is also illustrated by the fact that in the number of involved cities and companies with road test permits is increasing. In December 2021, self-driving vehicles were tested in nearly 200 cities worldwide, and up to 53 companies already have test permits in the road systems of the state of California (DMV, 2021). However, conducting tests on public roads, self-driving vehicles are still considered experimental technologies (Cohen, Stilgoe, & Cavoli, 2018); and the diffusion of self-driving vehicles depends not only on technological advancement but also on social acceptance

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(KPMG, 2018).

Understanding the motivations and reasons behind the customer acceptance of self-driving technology considered as crucial. Studies are often anchored at the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Stemmed from different variations of the TAM and UTAUT models, recent survey-based empirical studies on acceptance of self-driving technology include Baccarella et al. (2020), Choi and Ji (2015), Koul and Eydgahi (2018), Leicht et al. (2018), Madigan et al. (2017), Moták et al. (2017), Müller (2019), Nordhoff et al. (2020), Panagiotopoulos and Dimitrakopoulos (2018), Wu et al. (2019), and Zhang et al. (2021).

Although first-hand self-driving vehicle user experience is increasingly subject to examination, most of the studies are based on an analysis of empirical data from respondents who have not met a self-driving vehicle before. An exception is, for example Zoellick et al. (2019), where the applicants filled out the questionnaire after having experienced a self-driving vehicle ride with level 4 automation, or Buckley et al. (2018), where survey responses were gathered 20 min after a simulated experimental self-drive vehicle. Nevertheless, in-depth understanding of the consumer's intention to use self-driving vehicles would increase if the respondents also had personal experience related to the use. As Keszey (2020) puts in her systematic literature review, inconsistent results of different studies may be related to the difficulty for respondents to evaluate and estimate the consequences of a technology for which respondents lack empirical evidence.

The other set of methodological limitations are related to the subjective, perceptual nature of the survey, which can pose risks for method biases, which are among the key reasons of measurement error (Ketokivi, 2019; Podsakoff et al., 2003). Such biases can become critical issues when it comes to the measurement of variables – such as intention to use a self-driving vehicle – that are not directly observable or objectively measurable but self-reported (Jap & Anderson, 2003). Examples of these biases include inaccuracy (e.g., respondents lack of time or other resources to provide adequate responses) or social desirability bias, "the tendency of some people to respond to items more as a result of their social acceptability than their true feelings." (Podsakoff et al., 2003, p. 882).

To address these limitations of real-life experience of self-driving technology, we carried out an empirical study by inviting our respondents to participate a self-driving test ride. After reviewing the methodology used in the literature, we decided to use a combined data collection approach: Surveys were conducted before and after the event based on the widely-used Unified Theory of Acceptance and Use of Technology (UTAUT) model. Moreover real-time physiological measurements - electroencephalography (EEG) and eye-tracking (ET) - were also performed while participants were passengers in a self-driving vehicle. We decided to use these methods since, on the one hand, UTAUT-based questionnaires are the most widely accepted in the literature for the assessment of technology acceptance and, on the other hand, EEG and ET are the two most commonly used neuroscientific methods in this field.

The remainder of this paper is organized as follows. The following section presents the theoretical background of the study, followed by study's research methods. After the presentation of the results, the article concludes with a discussion of the study's theoretical contributions, managerial and policy implications, limitations, and suggestions for future research.

2. Theoretical background and preliminary hypotheses

2.1. Measuring technology acceptance using survey-based methods

Consumer acceptance of self-driving vehicles is a topic of increasing research interest, as indicated by the number of new related studies, that is, 494 in 2018, 709 in 2019, 910 in 2020, and 1080 in 2021, and it has already exceeded 1100 in 2022 in the international literature.[1] The conceptual foundation of understanding the consumer acceptance of new technology includes the theory of reasoned action (Fishbein & Ajzen, 1975), the theory of planned behavior (Ajzen, 1991), TAM (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008), or the UTAUT (Venkatesh et al, 2003; Venkatesh et al., 2012).

Widely used models in the investigation of consumer acceptance of self-driving vehicles in the economic literature are the TAM and UTAUT (Koul & Eydgahi, 2018; Müller, 2019; Smyth et al., 2021). These models identify Behavioural Intention (BI) – which shows how likely someone is to use a new technology – as their core dependent variable. BI is influenced by wide variety of the independent variables defined by the particular model. As Table 1 suggests, several variations of the TAM and UTAUT models have been used in prior studies. As evolved, these models are often amended with new independent variables.

In our research we use the UTAUT 2 model (Venkaetesh et al., 2012) which is the synthesis and updated version of the previously presented acceptance models. It is designed for understanding BI to use new technologies that are created for private use. The independent variables of the model in case of self-driving vehicles are as follows: Performance Expectancy (PE) stands for the level how much using a self-driving vehicle would improve one's everyday life. Effort Expectancy (EE) reveals how hard people assume using a self-driving vehicle would be. Social Influence (SI) helps understand how other people's opinions and suggestions effect one's BI towards self-driving vehicles. Facilitating Conditions (FC) are external factors that ease the use of self-driving vehicles, while Hedonic Motivation (HM) unveils how much fun it would be to ride in a self-driving vehicle. Utilitarian Motivation (UM) is a special factor in the model that expresses the value of activities one can engage in by not having to drive, but ride in a self-driving vehicle. Supposing that users will need to purchase self-driving vehicles in order to use it, Price-Value (PV) perception is also an important determinant of BI. In the theoretical framework all presented independent variables have a positive effect on BI. However, people will need to entrust self-driving vehicles their own lives and the lives of their loved ones, so Perceived Risk (PR) has a negative, while Perceived Safety (PS)

[1] https://www.sciencedirect.com/search?qs=AV%20technology%20acceptance Downloaded: January 4, 2023.

Table 1
Independent variables of the models measuring technology acceptance.

TAM 3 (Venkatesh & Bala, 2008)	UTAUT (Venkatesh et al, 2003)	UTAUT2 (Venkatesh et al., 2012)
Subjective Norm	Performance Expectancy	Performance Expectancy
Image	Effort Expectancy	Effort Expectancy
Job Relevance	Social Influence	Social Influence
Output Quality	Facilitating Conditions	Facilitating Conditions
Result Demonstrability		Hedonic Motivation
Computer Self-efficacy		Utilitarian Motivation
Perceptions of External Control		Price Value
Computer Anxiety		
Computer Playfulness		
Perceived Enjoyment		
Objective Usability		

has a positive effect on BI (Liu et al., 2019; Xu et al., 2018).

We can also find an example for eliminating some of the independent variables of the models. Based on the findings of Nordhoff et al. (2020) after examining a sample size of thousands involving several countries, the perceived simplicity of use does not influence BI. Madigan et al. (2017) have also arrived to similar conclusions; however, in their case, besides perceived simplicity, hedonic motivations also failed to have a significant impact on BI.

Most studies presented above have used an online questionnaire method, and so far, only a handful of people have actual experience with self-driving vehicles. When asked their opinion, they express their feelings based on their subjective assumptions, which can be misleading (Penmetsa et al., 2019). As Csizmadia (2021) points out, the ratio of people who have had direct interaction with self-driving technologies or advanced driving assistance systems is around 4–5% of the population.

2.2. Measuring technology acceptance using neuroscience

Neuroeconomics, as a subdiscipline of experimental economics, applies neuroscientific research tools in addition to involving psychologist researchers. Thus, the evidence gained can facilitate the mapping of hidden information as regards behavior examined by economics (Camerer, 2007). Such hidden information might be preference or emotions regarding certain products or situations which are often problematic to verbalize or indicate explicitly on a Likert-scale. In addition to survey methods, neuroscience can retrieve information on participants' affective and cognitive states by continuously monitoring changes in blood-oxygen level (functional

Table 2
Applications of neuroeconomics in consumer research.

Field	Topic	Author(s)	Used tool	Analysis
Neuromarketing research	Product perception	Alvino (2018)	EEG	Wine, consumer preferences, social influence
		Bruce et al. (2014)	fMRI	McDonald's, effect of package testing on mouthfeel, children
		Ford (2019)	fMRI	iPhone, product attachment, emotions
		Khusbaba et al. (2013)	fMRI, EEG, ET	Snacks, product characteristics, product preferences
		Yoon et al. (2006)	fMRI	Judgments of products and persons, comparison
	Consumer behavior	Ariely and Berns (2010)	fMRI	Excise goods, willingness to pay, reward center
		Barnett and Cerf (2017)	EEG	Film trailers, willingness to pay, forecast
		Pozharliev (2017)	EEG	Branded products, social influence
		Venkatraman et al. (2015)	fMRI	Advertising films, study of advertisement effect, forecast
		Vorster (2015)	EEG	Use of sound effects in branding
Neuroscience in autonomous vehicle research	Human-machine interaction (HMI)	Arakawa et al. (2019)	EEG, ET, HRPM	Simulation, switching driving modes, anxiety
		Lee and Yang (2020)	EEG	L3 AV, driving take-over alarm
		van der Heiden et al. (2018)	EEG	Simulation, reaction to external sounds, AV vs. driving, vs. in one place
		Yang et al. (2018)	EEG	Simulation, driving style, categorization
		Navarro et al. (2016)	ET	Simulation, AV vs. driving, attention
	Attitude and intention to use AV	Park (2018)	EEG	AV trust, positive vs. negative experience, trust can be rebuilt
		Stephenson and Eimontaite (2020)	ET	L4 AV, older adults, anxiety changes after testing
		Strauch et al. (2019)	ET	Simulation and AV, driving style, trust
		Hochman et al. (2020)	ET	Simulation, reactions of pedestrians to AV
		Cisler et al. (2019)	EEG, ET,	Driver's cognitive involvement during driving

Abbreviations: AV: Autonomous vehicle, HRPM: heart rate per minute, ET: eye tracking, EEG: electroencephalography, fMRI: functional magnetic resonance imaging.

magnetic resonance imaging – fMRI) or electrical activity (electroencephalography – EEG) of the certain areas of the human brain, as well as drifts in the movement pattern of the eye which otherwise cannot be controlled consciously. We demonstrate the spread of neuroeconomics with some examples in Table 2, highlighting the studies that have focused on consumer's perception of self-driving technology.

Developments in the measurement tools of psychology and neuroscience offer novel opportunities to examine aspects of behavior in real-world, actual situations, such as eye movements and the brain's electrical activity. These neuroscientific tools open up new venues in measurements related to self-driving vehicles. However, by using conventional laboratory measuring devices such as non-portable EEG, fMRI or eye-tracker, participants are forced to sit or lay in a fixed position without any possibility for natural movements, significantly reducing ecological validity of the measures. Most studies targeting perception of autonomous vehicles (AV) aimed to capture passenger travel experience in a self-driving car using videos or a simulator (e.g., Lee & Yang, 2020; Park et al., 2018; Seet et al., 2022). For example, Park et al. (2018) found that when the participants were passively sitting in a simulator as passengers of an autonomous vehicle, the ratio of higher frequencies in brain activity increased when the vehicle was moving in dangerous situations (e.g., violating traffic rules), as opposed to smooth driving. This suggests enhanced alertness and a more aroused state when the route became risky. Similarly, effective warning signals were also accompanied by enhanced ratios of higher frequencies, suggesting a higher level of arousal (Lee & Yang, 2020). In terms of affectivity, differences between activity of left and right activity at frontal brain areas (frontal alpha asymmetry, see Harmon and Gable, 2018 and Methods section) was noted to correlate with the need for control over the car, reflecting the trust toward the system (Seet et al., 2022).

Although studies in a simulation environment have the advantage of controllability in laboratory practice, this control is often at the expense of ecological validity (Xu et al., 2021; Zoellick et al., 2019). Nevertheless, the emergence of portable devices (e.g., mobile eye-tracker, EEG, smart watch etc.) not only allow participants to leave the laboratory and to move relatively freely but has enabled the "in situ" examination of physiological and biological reactions (e.g., Abdur-Rahim et al., 2016), thus providing an even more accurate picture of the reactions experienced during different situations such as a test ride in a vehicle. The application of such research tools thereby enables us to present unique responses to the questions raised by researchers on consumer behavior by revealing mental processes which are otherwise not observable in behavior or which cannot be consciously controlled (Plassmann et al., 2015). Another advantage is that they help develop significant economic forecasts based on the emotional reactions measured in a small sample size. For example, when compared to surveys, physiological data aimed at emotional reaction were shown to be more accurate in predicting choice behavior (Boksem & Smidts, 2015). Ramsøy (2019), however, claimed that the application of these methods should be complemented by classical quantitative and/or qualitative procedures. Accordingly, we have developed an experimental arrangement that can integrate both questionnaire and electrophysiological methods without significantly infringing on ecological validity.

2.3. Preliminary hypotheses

In our research participants were taken for a self-driving test ride of an autonomous vehicle. Surveys were conducted before and after the event based on the UTAUT2 model, and real-time EEG and eye-tracking measurements were also performed during the ride. UTAUT2 questionnaires were completed 1–5 days before the ride and immediately following the ride. PANAS (Positive and Negative Affect Schedule) questionnaires were completed immediately before and after the ride. We have formulated preliminary hypotheses as follows:

As an actual test ride can significantly influence the opinion formed about self-driving cars (Arakawa et al., 2019; Liu et al., 2019; Park 2018; Raue et al., 2019; Stephenson & Eimontaite, 2020; Strauch et al., 2019; Xu et al., 2018), we can assume that in the case of a questionnaire completed earlier (before trial), the respondents express different opinions on certain independent variables (especially about emotional factors); thus, their impact on BI is different than after the trial; therefore, we have stated our first hypothesis as

H1: Significance of factors affecting behavioral intention to use self-driving vehicles may be a subject of change due to respondents' test ride.

Neuroscientific methods were successfully applied in measuring attitudes towards autonomous vehicles (Park, 2018; Cisler et al., 2019; Strauch et al., 2019; Stephenson & Eimontaite, 2020; Hochman et al., 2020). However, using EEG and eye-tracking during in-situ autonomous driving is barely applied. Moreover, we intended to get a more complete picture of the psychological status of the respondents, therefore we have also filled-out the widely-used PANAS (Positive and Negative Affect Schedule) questionnaire. Therefore we must put to test the relationship between these psychological (independent) variables and the behavioral intention (dependent variable):

H2: Real-time neuroscientific (EEG & ET) methods and psychological tests (PANAS) can effectively explain the intention to use self-driving vehicles.

UTAUT2 is one of the most widely used model for analysing intention to use autonomous vehicles (Müller, 2019; Keszey, 2020; Smyth et al., 2021), although it is only applied based on questionnaire survey data collection. Combining UTAUT2 model with neuroscientific measures can be considered as a new approach. To confirm the legitimacy of this complex research methodology, we had to prove that we could obtain a more efficient solution that better explains the dependent variable (behavioral intention) if we combine questionnaires with neuroscientific methods:

H3: Neuroscientific measurements and the UTAUT2 questionnaire can be efficiently applied in combination, and the explanatory power of the model is higher than in the case of using only the UTAUT2 questionnaire.

Table 3
Variables used in the test.

UTAUT2 scale Name of variable	Its explanation and underlying original variables	Application to literature
Performance Expectancy–PE (Cronbach's α: 0.92)	It is useful in my daily life I would reach my destinations faster I would get about more easily Parking would no longer be a problem	Venkatesh et al. (2003)
Effort Expectancy–EE (Cronbach's α: 0.99)	It would be simple to learn to use it It would be user-friendly It would be easy to use It would not require a driving license	Venkatesh et al. (2003)
Social Influence–SI (Cronbach's α: 0.87)	I would be encouraged to use it I would proudly show it to others My acquaintances would have a positive attitude to me using it My friends would be interested whether I use it	Venkatesh et al. (2003)
Facilitating Conditions–FC (Cronbach's α: 0.99)	I have the financial conditions I have the required knowledge It is compatible with my technological devices I can count on the help of others	Venkatesh et al. (2003)
Hedonic Motivation–HM (Cronbach's α: 0.85)	It would be a real experience I would have fun while using it I would spend the time I save doing something fun I would enjoy using it	Venkatesh et al. (2012)
Utilitarian Motivation–UM (Cronbach's α: 0.93)	I would have more time to work I would have more time to consult with others I would have more time for my tasks I would have more time to run errands	Kapser and Abdelrahman (2020)
Price Value–PV (Cronbach's α: 0.73)	It would be available at a reasonable price It would be a good value for money I would buy it even with extra costs It will be more expensive than a traditional car The price will be the same for public transportation It is more expensive in the case of public transportation and taxi It would still be worth traveling by a self-driving taxi and public transportation with extra costs	Venkatesh et al. (2012)
The independent variables of the UTAUT 2 model adapted for the use of self-driving cars		
Name of variable	Its explanation and underlying original variables	Application to literature
Perceived Risk (anxiety)–PR (Cronbach's α:0.90)	How psychologically demanding using a self-driving car is (will be). I am afraid of using it It would cause more accidents I am afraid if there are only AVs on the road I am afraid it navigates in the wrong direction I am afraid the data collected about me will get into the wrong hands I am afraid my own AV causes an accident I am afraid it has a sudden malfunction I am afraid it will be hacked I am afraid what it would be like meeting with a conventional vehicle sitting in an AV I am afraid it would wrongly detect the movement of pedestrians and cyclists I am afraid it would not function properly under bad weather conditions	Liu et al. (2019)
Perceived Safety–PS (Cronbach's α: 0.87)	It would be dangerous to use it Its use would require increased attention I would feel safe in it It would decrease the number of accidents I would dare trust it with my life I would trust it with people important to me I would trust in the AV more than people I would only use it in urban environment I would only use it on open road	Xu et al., 2018
The dependent variables of the UTAUT 2 model adapted for the use of self-driving cars		
Name of variable	Its explanation and underlying original variables	Application to literature
Behavioral Intention–BI (Cronbach's α: 0.89)	I will try it when it becomes available I will travel by it regularly when it becomes available I would shift to using AV when it becomes available	Venkatesh et al. (2003)
Psychological & neuro-science factors		
Name of variable	Its explanation	Application to literature
Experienced positive emotions	Aggregated values of the scales related to positive emotions of the PANAS questionnaire: a total score of the 10 positive items of the scale. Higher values indicate a more positive current emotional state.	Gyollai et al., 2011; Wintersberger et al., 2016

(continued on next page)

Table 3 (*continued*)

UTAUT2 scale Name of variable	Its explanation and underlying original variables	Application to literature
Experienced negative emotions	Aggregated values of the scales related to negative emotions of the PANAS questionnaire: a total score of the 10 negative items of the scale. Higher values indicate a more negative current emotional state.	Gyollai et al., 2011; Wintersberger et al., 2016
Eye movement 1	Relative difference measured in the width of multifractal spectrum of eye movement between Human and Auto conditions in the first half *of the run.	Chhabra & Jensen, 1989
Eye movement 2	Relative difference measured in the width of multifractal spectrum of eye movement between Human and Auto conditions in the second half *of the run.	Chhabra & Jensen, 1989
EEG Arousal	The percentage change in the Auto condition compared to Human** The level of arousal was defined in each condition as follows: (activation measured on beta and gamma frequencies)/alpha activation.	Lee & Yang, 2020; Jun & Smitha, 2016; Kim et al., 2020; Minguillon, 2016; Park et al., 2018; Yi & Mohd, 2020
EEG Affectivity	The percentage change in the Auto condition compared to Human. Percentage change in the two conditions was calculated in the same way as arousal***	2018; Hartikainen, 2021; Seet et al., 2022; Sun et al., 2017
Driving conditions		
Human condition	A car that is capable of self-driving is driven by a human driver while the participant is sitting in the front right seat.	
Auto condition	An autonomous car is driven in self-driving mode while a driver is sitting still in the driver's seat and the participant is sitting in the front right seat.	

* First half was the path till the end of the road and then after a U-turn the second section was the way back.
**As the absolute differences between Human and Auto conditions can highly vary on an individual basis, which may lead to differences that are difficult to interpret, we defined the difference between the two conditions as a percentage difference, where 100% is the Human condition, and we compared the percentage of the Auto condition. Therefore, the data were normalized within an individual, and the percentage differences allow for an adequate comparison between participants.
***Affectivity was indicated by frontal alpha asymmetry, which was defined as the activation difference in the right and left frontal areas as follows: $F4_{log10}$-$F3_{log10.}$ (F4 refers to the electrical activity measured on the EEG electrode on the right frontal area, while F3 refers to that of the left frontal area).

3. Methods

3.1. Data gathering

3.1.1. Materials and tools for data gahtering

To gather data from the respondents by means of a survey, we were using the UTAUT2 (Venkatesh et al., 2012) and PANAS (Watson et al., 1988) questionnaires. This was followed by the vehicle (Tesla Model X) test-ride during which time we collected data using EEG and eye-tracking methods. Participants took the route twice: first, the ride was conducted with a human driver, while in the second part the self-driving mode was switched on and the driver released the steering wheel (Auto condition). After the ride we re-conducted the survey-based measurement.

3.1.1.1. UTAUT2 scale. We used the UTAUT2 model as a general framework for our primary research. We aimed to adapt this model based on the literature and combine it with psychological factors. The result is a complex model that covers multiple independent variables that influence the behavioral intention (BI). We summarize the variables used in the test later in Table 3, where we indicate the original variables (that also represent the questions from the survey) behind the artificial variables. The questions used to measure the UTAUT2 dimensions were based on a 5-point Likert scale in each case.

3.1.1.2. Positive and negative affection scale (PANAS). Emotional reactions were measured using the Hungarian version of PANAS (Gyollai et al., 2011; Watson et al., 1988) scale, where the respondent must express how much they agree with the statements about certain emotional states in a particular moment on a 5-point Likert scale (1–5). The scale contains 20 items: 10 referring to positive and 10 indicating negative adjectives. Higher scores on positive and negative items indicate a higher level of positive and negative mood, respectively. As PANAS was accomplished before and after the ride, the positive and the negative mood changes between timepoints before and after the ride were calculated for each participant and submitted to regression models.

3.1.1.3. Eye tracking. Since the end of the twentieth century, it has been known that eye movement correlates with a series of cognitive and affective processes, and it usually makes it an important source of information in the examination of cognitive behavior, learning, and emotional change. Here we can also differentiate between the approaches. Researchers either choose the location of eye focus and fixation times from the recorded data for further analysis, or they compare the change in the total energy input of eye movement and its entire spectrum with the development of behavior. The latter approach has produced a particularly high number of interesting results in the past decade. The movement of the eye, head, and hand shows a reliable connection to perceptual judgments, intention, comprehension and involvement (e.g., Freije et al., 2018; Palatinus et al., 2014; Story, 2016; Wallot et al., 2015). Spectral analysis of physiological fluctuations, such as eye movements shows a remarkable continuity between lower and higher levels of cognitive processes. We therefore found it crucial to study the data collected while traveling in self-driving vehicles relying on complex analytical procedures.

3.1.1.4. Eeg. In this study, we have simultaneously used a mobile EEG and an eye camera, which is already popular in marketing. EEG is based on the characteristic of the human brain being constantly active, even when one does not think of anything or during sleep (Luck, 2014). This activation can be registered from the scalp as electrical signals and can be measured noninvasively using EEG. EEG oscillations can be divided into different frequency bands, whose ratios reflect various affective (Harmon and Gable, 2018; Hartikainen, 2021; Sun et al., 2017) and cognitive states (Jun & Smitha, 2016; Kim et al., 2020; Lee & Yang, 2020; Minguillon, 2016; Yi & Mohd, 2020) from specified areas of the brain.

In our analysis, we applied two measures based on EEG to examine passenger experience in a self-driving car, which have also been proven to be reliable in previous studies. First, we used frontal alpha asymmetry to measure *affectivity*, which is often based on the activity of the alpha (frequency range of 8–12 Hz) between the right and left cerebral hemispheres. Higher values reflect motivation and approach, that is, more positive emotions, whereas lower values can indicate withdrawal (Harmon and Gable, 2018; Hartikainen, 2021; Sun et al., 2017). The other measure was related to *arousal*, that is, the level of general alertness and excitement. Given that the brain's higher-frequency electrical activity indicates a higher level of alertness and stress, if higher (beta and gamma: 13–60 Hz) frequencies dominate over lower ones (alpha: 8–12 Hz), the level of arousal is thus higher (Jun & Smitha, 2016; Kim et al., 2020; Lee & Yang, 2020; Minguillon, 2016; Yi & Mohd, 2020).

3.1.2. Participants and the procedure

In total, 25 healthy adults volunteered to participate the study (mean age = 32.23 years, SD = 9.13 years). All of them reported normal or corrected-to-normal vision and had no psychiatric or neurological problems. All participants received no monetary compensation, and all of them gave written informed consent before the study. This study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the United Ethical Review Committee for Research in Psychology (EPKEB), Hungary (ref. number 2020-89).

The test drive was conducted at a local airport. One to five days before the test all participants completed the UTAUT2 questionnaire online. Upon the participants arrival, after reading and signing the letter of consent, they completed the PANAS scale. After that, six EEG electrodes were attached to their heads (FPz, F3, F4 and Oz, and left and right mastoids as reference and ground, respectively) with a conductive gel (Ten20) in accordance with the 10–20 system, and eye tracking glasses were placed on the participants. We chose these 6 electrode positions because of two reasons. First, arousal and affective states are usually measured at certain electrode positions as a difference or average of a small number of electrodes typically at frontal areas (see below, e.g., Harmon and Gable, 2018; Jun & Smitha, 2016). Second, because of the limitations of the hardware (OpenBCI 4-channel Ganglion board), only 4 electrodes can be attached in addition to the reference and ground electrodes. To ensure that the devices are working properly, a baseline measurement was applied where the participants were shown 23 pictures successively inducing different emotions, which were selected from the Open Affective Standardized Images Set (Kurdi, Lozano & Banaji, 2017) database.

After the baseline measurement, the participant and two experimenters were seated into a self-driving vehicle (Tesla Model X), driven by a professional taxi driver. The participant was seated in the passenger's seat, while the experimenters were seated in the backseats. The participants did not have to perform any specific task during the test run; they only had to sit still as they would do as a passenger in general, ensuring that they avoided frequent blinking and bigger movements, as these could result in artifacts on the electrophysiological signals. The route was taken twice by the vehicle to the end of the designated L-shaped runway measuring 1.2 km $\times$ 30 m and back: first, the driver was driving (Human condition), and in the second round, the self-driving mode was switched on and the driver released the steering wheel (Auto condition). At the end of each run, after the participant left the vehicle and the EEG and eye tracking glasses were removed, they completed the PANAS and UTAUT2 questionnaires once again.

3.2. Data analysis

3.2.1. Processing eye-tracking data

From the raw eye-tracking data, we selected the less noisy medium section, including 5000 data points for each test, and conducted a direct multifractal spectrum analysis as discussed by Chhabra and Jensen (1989). Acceptable noise limits were identified following the manufacturer's recommendations (Pupil Labs GmbH). Under both conditions, we separately analysed the data recorded before and after the U-turn at the end of the runway. To compare the human-driven and autonomous test runs, we calculated the difference in the multifractal spectrum width and the ratio of the differences in the percentage for each subject. Finally, we included the multifractal spectrum width and the differences in the comparison between the two conditions as predictors while building the statistical models.

3.2.2. Processing EEG data

The continuous EEG was filtered offline; a bandpass filter (7–48 Hz, 9th-order Butterworth) was then applied to the data as this particular range characterized the frequencies of our interest. After filtering the whole blocks, continuous data were segmented into 4-second epochs with 2-second overlapping parts. Epochs with a signal range exceeding ±100 μV (typically due to movement or blink artifacts) were excluded from further analysis. Power spectral densities (PSDs) were calculated for alpha (8–12 Hz), beta (13–30 Hz), and gamma (30–45 Hz) band ranges using Welch method. For each epoch, an index for (1) affectivity and (2) arousal was computed.

Affectivity corresponded to frontal alpha asymmetry and was calculated as the difference between $\log_{10}$ transformed values of F4 and F3, with higher values representing a more positive emotional valence (Harmon and Gable, 2018). As higher frequencies were found to index a more aroused state in the frontal areas (Jun & Smitha, 2016; Lee & Yang, 2020), arousal was defined as the ratio of PSD in the beta and gamma ranges to the alpha range at the averaged F3 and F4 electrodes. To change the affectivity and arousal from Human to Auto condition between participants, we have calculated the percentage of activation change between the Human and Auto conditions. Because of excessive amount of movement artefacts or technical issues during the ride (e.g., lost signal between the laptop and the EEG device), only EEG data of 17 participants could be submitted into further analysis.

4. Results

Firstly, reliability measurement were conducted on the scales used for measuring technology acceptance. The results as well as all the original underlying variables of the model are summarized in Table 3. All Cronbach's alpha values (see in first column of Table 3) are above the threshold; therefore the internal validity of our measurement is accepted.

We tested the first hypothesis (H1: *Significance of factors affecting behavioral intention to use self-driving vehicles may be a subject of change due to respondents' test ride.*) using a multivariate linear regression model, which included the dependent variable of behavioral intention (BI) to use, while independent variables of the traditional UTAUT2 model were included as explanatory variables. We compared the results of two regression models based on the questionnaires completed before (1) and after (2) the ride. We have found that the explanatory power of the model increased (before: $R^2 = 0.628$, F-test = 10.6; p-value = 0.001 vs after: $R^2 = 0.789$, F-test = 2.815; p-value = 0.037 – see in Table 6) when we indicated the intention to use based on the values after the test run.

Before analyzing the partial effects of the explanatory variables, we have checked their independence, avoiding a harmful level of multicollinearity in the model. We conducted this analysis based on the VIF (variance inflation factor) values. As the VIF measure lined multicollinearity to an explanatory variable, we addressed it by excluding the variable (Social Influence – SI) with the highest VIF value (6.9), thereby decreasing multicollinearity below the threshold, which is 5 (Shrestha, 2020) (see Table 4).

The model developed from the questionnaire completed after the ride had a higher explanatory power (0.628 vs 0.789) than that which relies on the responses before the test ride; furthermore, the impact of the explanatory variables is also different. It is also interesting to note that before the ride the functional factors (i.e., Performance Expectancy [0.446] and Effort Expectancy [0.410] in Table 4) had a significant effect on the intention to use. While after the test run, Hedonic motivation [0.512] became the most significant explanatory factor. Accordingly, we accept hypothesis H1.

In the analysis of the second hypothesis (H2: *Real-time neuroscientific (EEG & ET) methods and psychological tests (PANAS) can effectively explain the intention to use self-driving vehicles*), we have also set up a regression model but included only the neuroscientific and psychological factors as independent variables, while the dependent variable (BI) remained the same as in H1. We have used the EEG results to calculate the relative change of affectivity and arousal values of participants when changing from Human to Auto conditions. We were interested in whether these relative changes indicated by the measures alone can explain the intention to use, and whether the positive and negative emotional changes measured by the PANAS questionnaire substantially improve the explanatory power of the model. Examination of 17 people with satisfactory EEG and eye-tracking data shows that the answer to both questions is "yes." Nevertheless, the explanatory power of the model relying merely on data from EEG and eye tracking is deemed to be not particularly high (50%). With the inclusion of the emotional changes measured using the PANAS questionnaire in the model, the explanatory power increased [0.647]. Consequently, the model relying only on psychological procedures also proved to be applicable as the intention to use has been closely linked to the total of psychological explanatory variables. (Note: This explanatory power [0.647] exceeded the one from UTAUT2-BEFORE model [0.628] but was lower than the one from UTAUT2-AFTER model [0.789]).

We have also determined the independent variables with the highest direct effect in the models based on merely psychological measurements. The results are summarized in Table 5.

Table 4

Standardized regression coefficients and the VIF values of the variables of the UTAUT 2 model on Intention to use self driving vehicle.

Independent variable	UTAUT2 questionnaire filled out BEFORE test ride β	UTAUT2 questionnaire filled out AFTER test ride β	UTAUT2 questionnaire filled out BEFORE test ride VIF	UTAUT2 questionnaire filled out AFTER test ride VIF
Performance Expectancy–PE	0.446**	−0.110	1.273	1.804
Effort Expectancy–EE	0.410*	0.287	2.141	1.893
Social Influence–SI	0.222	–	2.081	–
Facilitating Conditions: FC	−0.147	−0.099	2.475	3.872
Hedonic Motivation–HM	0.069	0.512*	1.855	2.881
Utilitarian Motivation–UM	−0.149	0.012	1.327	1.607
Price Value–PV	−0.005	0.120	1.820	4.744
Anxiety	0.069	0.164	1.303	1.953
Perceived Safety–PS	0.164	0.369	2.286	2.484

**p-value < 0.05; * p-value < 0.1.

Table 5
Standardized regression coefficients (β) and the VIF values of the independent variables of models based on psychological measurements.

Independent variable	EEG + eye tracking β	PANAS + EEG + eye tracking standardized regression coefficients β	EEG + eye tracking VIF	PANAS + EEG + eye tracking VIF
EEG arousal	0.212	−0.054	2.882	4.864
EEG affectivity	0.165	0.174	1.342	1.437
Experienced negative emotions based on PANAS	–	−0.202	–	2.981
Experienced positive emotions based on PANAS	–	−0.496	–	1.679
Eye tracking 1st route section	−0.704	−0.916	1.326	2.520
Eye tracking 2nd route section*	0.407	0.333	3.34	3.693

* The two route sections were identical (first section till the end of the road and then after a U-turn the second section was the way back). The novelty effect could have been higher during the first route section, while the participants could have habituated during the second route section.

The eye-tracking data measured in the first route section and the positive emotional change measured by PANAS were determined to have the strongest impact on the intention to use. The model shown in Table 5 indicates that the intention to use was strongly predicted by the extent of change in the experienced positive emotions (-0.496) based on PANAS compared with the state before the ride. As the negative values show that the individual's positive emotions increased after the ride, the results indicate that a stronger intention to use can be assumed as an effect of heightened positive emotions. The predictive strength of eye tracking data was manifested in the relative difference in the first impressions between the two conditions (Human and Auto) because the BI was predicted by the differences measured in the first half of the route. The negative values suggest that those people for whom the difference between the two conditions was smaller in the initial stage of the trial expressed a stronger intention to use. Based on these results we can accept H2.

To test hypothesis H3 (*Neuroscientific measurements and UTAUT2 questionnaire can be efficiently applied in combination, and the explanatory power of the model is greater than just in the case of the UTAUT2 questionnaire*), we combined all independent variables to construct the model with the highest explanatory power such that the partial effects can be interpreted.

In Table 6 several combinations of methods are shown. From these combinations the use of UTAUT 2 model with follow-up (AFTER) data collection and EEG arousal measurement proved to be the best choice, as the explanatory power of the model formed based on these variables related to the intention to use (0.966) is considerably higher than any other combinations. It also means that adding EEG Arousal measurement to the UTAUT2 follow-up measurement raises the explanatory power of the model (0.966 vs 0.789). Accordingly, we accept hypothesis H3, that is, the questionnaire procedure based on the UTAUT2 can be efficiently applied in combination with the psychological measurements.

An interesting result is obtained when we investigate which independent variables have the greatest impact on the intention to use in the different models (Table 7). The effect of Hedonic Motivation was strongest (0.512) in the AFTER model, while in the most effective (EEG + UTAUT) model Perceived Safety (0.600) and Anxiety (0.439) outweighed Hedonic Motivation (0.318).

It is important to note that due to the lack of prior studies with the present arrangement, no data-based a priori calculation to estimate optimal sample size was possible. The sensitivity analysis calculated by G*Power 3.1.9.4 (Faul, Erdfelder, Lang, and Buchner, 2007) revealed that multiple linear regression with 10 predictors and with a sample size of 17 was sufficient to detect effects of Cohen's $f = 1.748$ ($\eta^2 = 0.754$) with 80% power. That is, small or medium sized effects might have remained undetected.

5. Discussion

Based on the results of H2 and H3 it is insightful to complement the UTAUT2 method with real-time neuroscientific data and psychological analyses in order to get a more accurate picture on participants intention to use autonomous vehicles. While the commonly used method (preliminary UTAUT2 questionnaire survey) is statistically suitable to explain intentions to use autonomous vehicles ($R^2 = 0.628$), it explains it through other factors than the more efficient ($R^2 = 0.966$) complex method. In the former case, functional characteristics dominate the behavioral intentions (Performance Expectancy and Effort Expectancy) while in the later

Table 6
Comparing the explanatory power of each regression model.

Model	Multiple correlation, R	Explanatory power, R^2	Adjusted R^2	Standard error of the estimate	ANOVA p-value
BEFORE (UTAUT2 questionnaire)	.793[a]	0.628	0.405	0.62292	0.037
AFTER (UTAUT2 questionnaire)	.888[a]	0.789	0.602	0.60511	0.023
PANAS + EEG relative change + eye tracking	.804[a]	0.647	−0.060	0.96321	0.578
EEG relative change + eye tracking	.707[a]	0.500	0.101	0.88723	0.397
AFTER (UTAUT2 questionnaire) + EEG Arousal	.983[a]	**0.966**	0.887	0.32896	0.032

Table 7
Comparing the impact of variables defining the intention to use according to each model.

Models	UTAUT2 questionnaire filled out BEFORE test ride β	UTAUT2 questionnaire filled out AFTER test ride β	UTAUT2 questionnaire filled out AFTER test ride + EEG Arousal β
Dependent variable	Behavioral intenention (BI) before use of autonomous vehicle	Behavioral intenention (BI) after use of autonomous vehicle	Behavioral intenention (BI) after use of autonomous vehicle
Independent variable			
Performance Expectancy–PE	**0.446****	−0.110	−0.061
Effort Expectancy–EE	**0.410***	0.287	**0.552****
Social Influence–SI	0.222	–	–
Facilitating Conditions: FC	−0.147	−0.099	0.190
Hedonic Motivation–HM	0.069	**0.512***	0.318
Utilitarian Motivation–UM	−0.149	0.012	–
Price Value–PV	−0.005	0.120	–
Anxiety	0.069	0.164	**0.439***
Perceived Safety–PS	0.164	0.369	**0.600***
EEG Arousal	–	–	0.138

Note: We removed three variables showing high multicollinearity (SI, UM, PV) from the EEG + UTAUT model.
**p-value < 0.05; * p-value < 0.1.

complex model (featuring EEG measurement) deeper emotional factors (Anxiety, Perceived Safety) proved to be significant.

Regarding the contribution of EEG data to the UTAUT2 model, we can conclude that when the change in arousal from Human to Auto condition was added to the UTAUT2 results, explanatory power increased. Although the predictive effect of arousal per se in the model was deemed insignificant, it may improve the explanatory power, indicating that considering participants' arousal during in-situ experience of the self-driving technology is an important factor when predicting the intention to use. This result also expands the literature on the relationship between AV acceptance and EEG signals as an enhanced level of higher frequencies (Park et al., 2018) and frontal alpha asymmetry have already suggested to be indicators of trust (Seet et al., 2022). Our results are also consistent with the findings of Stephenson and colleagues (2020), who used eye tracking to show that trial and error changes subjects' perceptions and that anxiety is an important influencing factor.

To summarize, while traditional questionnaire methods can identify the factors that respondents consider to influence their (future) intention to use self-driving technology, the real influence is more complex. The questionnaire indicates that without a trial, the perceived functional benefits are an important factor; however, after a trial, the perceived experience is more important. Nevertheless, when supplemented with neuroscientific methods, we see that fear and anxiety are (also) found to be determining factors.

Our results can be regarded as primary and relevant pilot results, whose obvious limitations are the measurement devices and time required for data collection. The methodological preparedness required for evaluating the physiological data is also a drawback because it is currently not possible to achieve a sample size similar to a questionnaire survey on technology acceptance.

6. Conclusions

This study focuses on how the possibility of testing an autonomous vehicle influences technology acceptance. In this study, we aimed to complement the widely accepted UTAUT2 model with psychological measures in order to better explain future intention to use AV. The novelty of our research method lies in introducing a complex method that combines the traditional UTAUT2 framework with innovative psychological measures (EEG and eye-tracking) leading to a model with higher explanatory power of technology acceptance.

Accordingly, we conducted an experiment in which we examined our research subjects' technology acceptance using the UTAUT2 methodology combined with physiological measurements. Our participants were taken as passengers in a self-driving vehicle for a test ride while we conducted EEG and eye tracking measurements on them and also filling-out UTAUT2 and PANAS surveys with them before and after the ride. According to our regression model, we were able to achieve high explanatory power (0.966) if the physiological (namely EEG arousal) measurements were used in combination with the UTAUT2 questionnaire that was completed after the drive (and not before that). It is also worth noting that depending on the method used, different factors proved to be important in explaining future intention to use. Functional factors seemed to be important when using solely UTAUT2 method without test-drive, while the role of emotional factors were identified crucial upon testing an autonomous vehicle.

Our primary results also highlighted that forming conclusions about attitudes towards autonomous technology by merely asking individuals who never had the opportunity to experience the ride in a self-driving vehicle might be misleading. Accordingly, further research on the topic by simulating real-life situations is worthwhile, as our results suggest that there is a substantial difference between hypothetical (self-reported) and real (biologically measurable) reactions when testing self-driving vehicles. In this context, we thus recommend testing on a more complex test course or even testing a complete driverless self-driving situation using both a questionnaire and neuroscientific tools.

In this study, we aimed to focus on the importance of social science research aspects related to self-driving vehicles and provide the research community with a basis for further research that can effectively combine neuroscience and traditional survey methods. Our results are also useful for practitioners. In addition to technical solutions, it is important for companies developing self-driving cars to (responsibly) innovate considering the needs (both desires and fears) of potential passengers. Moreover, social support essential for the uptake of self-driving technologies cannot be achieved without understanding the attitudes of a (potential) consumer toward the new technology. The fact that while before the test ride mainly the functional aspects of the vehicle were more predictive regarding the intention the use, after the test ride the emotional factors became dominant, leads to two conclusions. Firstly, and most importantly, considering individuals' real-life experiences based on being passenger in self-driving car is essential –while on the other hand, making policies as merely asking them without having any personal experience can be easily misleading. Secondly, as in-situ emotions are often difficult to verbalize or to assess by questionnaires, neuroscientific measurements are promising tools in consumer acceptance research by complementing existing methods.

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Miklós Lukovics: Writing – review & editing, Funding acquisition, Project administration. **Szabolcs Prónay:** Writing – original draft, Writing – review & editing. **Zoltán Majó-Petri:** Supervision. **Péter Kovács:** Formal analysis. **Tamás Ujházi:** Writing – original draft. **Márta Volosin:** Investigation, Data curation, Writing – review & editing. **Zsolt Palatinus:** Investigation, Data curation, Writing – review & editing. **Tamara Keszey:** Validation.

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

The data that has been used is confidential.

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