Physiological Measurements in Social Acceptance of Self Driving Technologies

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Abstract

The goal of the present study is to examine the cognitive/physiological correlates of passenger travel experience in autonomously driven transportation systems. We investigated the social acceptance and cognitive aspects of self-driving technology by measuring physiological responses in real-world experimental settings using eye-tracking and EEG measures simultaneously on 17 volunteers. A typical test run included human-driven and autonomous conditions in the same vehicle, in a safe environment. In the spectrum analysis of the eye-tracking data we found significant differences in the complex patterns of eye movements: the structure of movements of different magnitudes were less variable in the autonomous drive condition. EEG data revealed less positive affectivity and slightly higher arousal in the autonomous condition compared to the human-driven condition. Correlates with personality traits are also discussed. These preliminary findings reinforced our initial hypothesis that passenger experience in human and machine navigated conditions entail different physiological and psychological correlates, and those differences are accessible using state of the art in-world measurements. These useful dimensions of passenger experience may serve as a source of information both for the improvement and design of self-navigating technology and for market-related concerns.

Introduction

Autonomous transportation is a field of innovation being rapidly advanced in the past decade. Most major car manufacturers are racing towards mass production of partly or fully autonomous vehicles. Moreover, mobility providers like Uber or Lyft have started their own programs, and tech companies like Google or Nvidia have also entered the field. Despite all the effort that goes into the engineering and the design of self-navigation, there are concerns about the general acceptance of autonomous vehicles. Those concerns include uncertainty whether the general public would be willing to purchase semi or fully autonomous cars at a rate that justifies mass production, and ethical uncertainty about safety and responsibility, among others. Since the advent of testing self-driving cars in real traffic situations there have been numerous efforts to assess acceptance, anxiety, arousal and other emotional aspects of this particular new technology [1]. Besides asking people to report their feelings and experiences, a reliable source of information is tracking biological measures like heart rate, muscle activity, eye movements, or electroencephalography (EEG) signals. Up until very recently, the non-portability of certain advanced neurological and behavioral techniques such as motion tracking, EEG or electromyography (EMG) often confined these investigations to the laboratory. Instead of real-world passenger experience, researchers often used video recordings, virtual reality (VR) or computer simulations [2-5]. However, recent improvements in measurement technology have made it viable to record these biological signals in the actual vehicles in focus. Our study is aimed 1) establishing a viable research method for the psychological and physiological measurement of passenger experience in self-navigating vehicles and 2) finding useful dimensions of covariability in the recorded data. The overall aim of our research is to establish a set of measurements that are sensitive in gauging affective engagement in experiencing autonomously driven passenger cars.

Self-driving vehicles are radical innovations which according to our current knowledge will overturn the daily lives and decades-old habits of all people in developed countries – whether they are involved in transport as drivers, cyclists, pedestrians, passengers, etc. [6]. Technological development related to self-driving vehicles has greatly accelerated recently: at present, self-driving vehicle tests are being conducted in nearly 200 cities - a figure which has doubled in one year. Hence, it seems that more developers are in the last phase of technical development, and are ready to enter production [7].

However, with a very few exceptions, developers focus solely on technological development, thus the spread of self-driving vehicles depends not only on the technological development shown, but also on legislative framework, infrastructure, and social acceptance [8]. One of the most important factors regarding innovation diffusion are decisions on innovation: the acceptance or the rejection of innovations and their expansion is based on people's judgments and decisions [9]. Therefore, development work shall be extended in the direction of mapping social acceptance as accurately as possible, thereby accelerating social adaptation in the interest of the society and its members' ability to process the projected drastic change.

In the last decades of the 20th century Information Systems (IS) were adopted in both organizational and domestic environments. Behavioral researchers wanted to know which factors influenced the acceptance and use of these new technologies. As a result, several technology acceptance research models were developed. Initially, there were the Theory of Reasoned Action (TRA) [10], and the Theory of Planned Behavior (TPB) [11]. Davis et al. [12] merged these theories into the Technology Acceptance Model (TAM). All the above-mentioned models assume that the actual use of a new technology depends on one's behavioral intention (BI) to apply the technology itself. BI is directly moderated by one's attitude towards use (A). In the TAM model, Perceived Ease of Use (PEU) and Perceived Usefulness (PU) have a direct aggregated moderating effect on A. In the TAM 2 model, PEU is described by Davis [12]; later [13] described PU. Venkatesh et al. [14] proposed a unification of the existing technology acceptance models and presented the Unified theory of Acceptance and Use of Technology (UTAUT) adding Social Influence (SI), Facilitating Conditions (FC) and moderating variables (Age, Gender, Experience and Voluntariness) to the model. The UTAUT 2 research model [15] is designed to allow researchers to investigate consumer acceptance and the use of new technologies, adding new moderating factors (Hedonic Motivation, Price Value, Habit) and removing one (Voluntariness of Use) from the model.

The UTAUT 2 model is widely used to predict technology acceptance and thus future behaviour. However, it is an interesting question how well the commonly used questionnaire survey is capable of collecting real and valid information. Consider for example the reporting of the subject's own emotional state (called Hedonic motivation in the UTAUT 2 model). Respondents often find it difficult to identify and report their current emotional states. This is especially true when they were asked about their future (expected) emotional states when traveling in a self-driving vehicle. Concurrently, Nordhof et al [16] asked 9,118 car drivers from eight European countries using the UTAUT2 model to explain public acceptance of conditionally automated (L3) cars and found that hedonic motivation was identified as the strongest predictor from all UTAUT 2 variables of individuals' behavioural intention. Their results indicated that individuals who found conditionally automated cars to be fun and enjoyable were more likely to intend to use them. However, the method for measuring hedonic motivation was still the traditional online survey.

On this basis, it is worth considering what alternative data collection methods could be used to explore these emotional motivations. For this purpose, the UTAUT 2 model can be taken as a framework, where variables can be measured with a more holistic approach – for example, to examine emotional responses by neuroscientific methods rather than direct interviewing. Most studies on attitudes and trust towards autonomous technology utilize self-reporting questionnaires (e.g. [17, 18]). This approach has several limitations: first, the vast majority of participants respond without any prior experience as a passenger or driver of self-driving vehicles. Second, social desirability factors also might bias the results, therefore the objectivity of such data might be questioned. Recording physiological responses like EEG, galvanic skin response (GSR) or eye movements might be a useful method for eliminating such biases, and results of these measurements can be easily compared with self-reported data. Although a growing amount of research attempted to measure passengers' biological reactions in autonomous vehicles either utilizing EEG (e.g. [3, 4]) or eye-tracking methods [19, 20], we are not aware of any studies in which EEG and eye-tracking data were recorded simultaneously.

Eye movements indicating emotional and cognitive transitions

Muscle movements in perceptual systems including the head, hands, and feet have been established to indicate cognitive and affective states and transitions. Spectral analyses of head movements and eye movements were repeatedly shown to indicate intentional, goal related cognitive transitions such as problem solving, recognition, or comprehension. The general reasoning behind using complexity measures and spectrum analysis on continuous physiological data focuses on the source of cognitive and emotional change. Such changes are likely to be distributed within the complex network of physical, electro-chemical, nervous, muscular, and behavioral interactions. These are fundamental to complex systemic behavior, such as weather patterns, ecological dynamics, stock market fluctuations, or functions of the nervous system. Natural systems often exhibit power-law distributions and the variation of their components is correlated across both spatial and temporal scales [21, 22]. These correlations allow inquiry into the number and strength of interactions between the active components. In recent years, the concept of multifractality has become more popular in modeling, exploration, and prediction of complex dynamical system behavior [23, 24]. In psychology, multifractal concepts and tools became available right after the introductory reports (i.e. [25]) and they were followed by tutorials and practical guidance [26, 27].

Differences in the distribution of fractal dimension and the width of the multifractal spectrum have been reported as significant and reliable markers in various cognitive tasks including problem solving [28], magnitude perception [29, 30], perceptual intent [31], visual recognition [32], comprehension [33], and memory [34]. Inspired by these relatively recent findings, our experimental research methods on the eye-tracking data included fractal and multifractal analysis.

EEG signatures of emotional and cognitive transitions

The human brain is constantly active, resulting in electrical signals that can be measured from the scalp by EEG. The EEG oscillations are mainly classified according to their frequency bands: for example, the delta band is referred to as activation below 4 Hz, the theta band reflects activity between 4-8 Hz, the alpha band between 8-12 Hz, beta between 13-30 Hz, and activity higher than 20 Hz is referred to as the gamma band [35].

Numerous studies target EEG correlates of emotional and motivational states by differences in alpha band power between the right and left hemispheres [36, 37]. Frontal alpha asymmetry is a result of the subtraction of left frontal alpha power from right frontal alpha power after log-transforming the values to normalize distributions (log F4 minus log F3). The result is referred to as relative left or relative right frontal activity: when the result is more positive, relative left activation is present and when the result is more negative, relative right activation is present. High scores therefore indicate more positive or approaching attitudes while lower scores indicate more negative or withdrawal attitudes [37, 38].

When classifying mental states or cognitive processes from relaxed to alerted or stressed states, usually the ratio of higher frequency (beta, gamma) and lower frequency (alpha, theta) powers are compared [39, 3]. Lower frequencies are dominating in more relaxed states while higher frequencies are present in more aroused or stressed states. For example, increased beta/alpha ratio [40, 30], decreased alpha/beta and theta/beta ratio [41] or increased relative gamma ratio [42] was found to correlate with stress level. Higher relative gamma was also detected during enhanced attention and concentration [3].

Several studies record EEG while participants are exposed to self-driving technology, mostly by sitting in a simulator [2-5]. For example, Park and colleagues [4] found an increasing beta-alpha power ratio when a participant was passively watching positive scenarios (the car performing smoothly on a highway) and negative scenarios (the same car driving erratically and violating common rules of the road) of self-driving cars, revealing elevated stress levels when the participants were exposed to simulated dangerous situations. In a similar simulator study, the most effective takeover warning signals were accompanied by enhanced ratios of higher frequencies, suggesting enhanced stress, attention, and alertness [3].

Most recently, Seet and colleagues [5] investigated the impact of autonomous vehicle malfunction on human trust by combining EEG and self-reported questionnaires in a simulation environment. During the simulation, participants actively drove the vehicle in an urban environment and from time to time, scenarios with malfunctions (e.g. the vehicle drove at high speed through junctions or even crashed) occurred. In the Conditional Automation Driving phase, participants were able to take over control when needed, while in the Full Automation Driving condition no takeover function was present. Results showed that participants' preference was significantly higher toward the situation when they were able to take over control. Besides, the frontal alpha power reduction in the right but not in the left hemisphere during malfunctions in the fully automated condition can also be interpreted as an enhanced motivation of the driver towards controlling the vehicle.

Since we have limited experience with autonomous navigation systems and real-world physiological measurements our hypotheses were outlined carefully. First, we expected that our complexity measure — the multifractal spectrum width — would be sensitive to possible differences in the human driver versus autonomous driving conditions. Looking at the MF width literature, we could not predict the exact direction of the difference. Second, we expected to find that the novelty and excitement of the experience would manifest itself in higher levels of valence and arousal in the EEG data. Third, we expected that some personality or anxiety measures in psychological surveys would correlate with physiological measures.

Results

Eye tracking results

Multifractal spectra of one-dimensional eye displacement data were calculated for the first and second halves of each trial. Out of the 17 participants, in three cases our equipment produced suboptimal data quality with less than 0,8 mean confidence level in capturing the real position of the pupil (where 1 designates maximum confidence). These three cases were not excluded since their exclusion did not make difference in the overall results. Binomial logistic regression using the MF spectrum width as a predictor showed a significantly narrower spectrum for the auto condition $Z = -1.99$, $p = 0.046$. All VIF values were near to 1.0 with a tolerance of 0.99 indicating that collinearity was not a problem. The difference between the two conditions was slightly more pronounced in the second half of the trials but as a factor, the segment of the ride did not appear to contribute to the results.

Beside the measures reported above, differences between the MF spectrum width in the *Human* and *Auto* conditions were calculated for each participant. Ego-resilience was in a significant negative relationship with the

MF spectrum width difference ($r_s(15) = -0.49$, $p = 0.05$) showing that more ego resilience was related to less difference in the eye-movement structure in the two conditions. The overall MF spectrum width in the *auto* condition showed a relatively strong negative correlation with Trait Anxiety ($r_s(15) = -0.54$, $p = 0.02$) indicating that the more overall anxiety a participant reported the narrower their eye movement MF spectra were, but only when the car was navigating by itself.

EEG results

Differences between the first and second halves of the route were compared in the two conditions by Condition (Human/Auto) × Part (First/Second) ANOVAs separately for frontal alpha asymmetry (affectivity) and arousal values. Interactions were followed up with paired t-tests. Spearman rho correlations were calculated between affectivity and arousal values and questionnaire' scores. Affectivity values are presented in Fig 1a while arousal values are presented in Fig 1b.

Affectivity (frontal alpha asymmetry)

The Condition × Part ANOVA showed a marginally significant Condition main effect: ($F(1, 16) = 4.197$, $p = 0.057$, $\eta^2_G = 0.028$), suggesting slightly larger avoidance, and less positive reactions were present when the car was driving in autonomous mode. No other effects were significant (Part main effect: $F(1, 16) = 4.197$, $p = 1.317$, $\eta^2_G = 0.268$; Condition × Part: $F(1, 16) = 0.547$, $p = 0.47$, $\eta^2_G < 0.001$).

Frontal alpha asymmetry showed significant negative correlation with **Agreeableness** ($r_s(15) = -0.489$, $p = 0.046$), with **Ego-Resiliency** in general ($r_s(15) = -0.590$, $p = 0.013$) and its sub-scale Active Engagement With The World ($r_s(15) = -0.519$, $p = 0.033$) in the Human condition. In the Auto condition, affectivity correlated significantly with **Spielberger Trait** ($r_s(15) = 0.491$, $p = 0.045$) and **State** ($r_s(15) = 0.550$, $p = 0.022$) Anxiety. Besides these results, significant negative correlation was present with **Ego-Resiliency** in general ($r_s(15) = -0.504$, $p = 0.039$). No other correlations were significant (all r_s values < 0.470, all p values > 0.057).

Arousal

The Condition × Part ANOVA showed significant Condition main effect ($F(1, 16) = 4.649$, $p = 0.047$, $\eta^2_G = 0.023$) and more importantly, the Condition × Part interaction was also significant: $F(1, 16) = 4.601$, $p = 0.048$, $\eta^2_G = 0.003$. The follow-up t-test indicated that arousal decreased in the second half of the route in the Human condition ($t(16) = 0.427$, $p = 0.066$) while arousal was kept high in the Auto condition ($t(16) = 0.427$, $p = 0.675$). The Part main effect was not significant ($F(1, 16) = 2.132$, $p = 0.116$, $\eta^2_G = 0.005$).

Arousal values in the Human condition showed significant positive correlation with **Agreeableness** ($r_s(15) = 0.565$, $p = 0.018$) and significant negative correlation with change on **PANAS positive scale** between before and after the ride ($r_s(15) = -0.498$, $p = 0.042$) suggesting that higher arousal was accompanied with higher agreeableness and a larger change on PANAS positive scale towards positive values.

In the Auto condition, significant positive correlations were present between arousal and **Neuroticism** ($r_s(15) = 0.524$, $p = 0.031$) and **Agreeableness** ($r_s(15) = 0.660$, $p = 0.004$) factors, with **Locus of control** ($r_s(15) = 0.490$, p =

0.046) and with **PANAS positive scale** following the ride ($r_s(15) = 0.559$, $p = 0.020$). No other effects were significant (all r_s values < 0.475, all p values > 0.054).

Questionnaires

As the results of the self-reported questionnaires were analyzed in context of the physiological measurements only, we do not detail the further correlations between certain questionnaires or other variables. For the summary of survey data see Table 1.

Discussion

The present study aimed to investigate people's experiences and feelings while being a passenger of an autonomous vehicle as indexed by MF power spectral density patterns and by self-reported questionnaires. We found an overall narrower MF spectrum width in the auto condition. Regarding EEG, frontal alpha asymmetry values were higher in the Human condition compared to the Auto condition, while arousal showed the opposite pattern: it was slightly higher in the Auto condition. In addition, personality factors like openness, anxiety, or ego-resilience were identified as potential correlates of passengers' experiences in autonomous vehicles.

Eye-tracking data indicated an overall narrower MF spectrum width in the Auto condition. Narrower spectra are often characterized as indicative of fewer governing forces in the dynamical system. The exact source of this difference is unclear but we hypothesize that it could be the effect of the self-driving mode, or have a purely psychological cause. More testing is required to identify the discrepancy, possibly providing a meaningful measure in the future. The psychological survey data also had some notable co-variation with the MF spectrum of the eye movements. It is slightly counterintuitive that people who reported higher overall anxiety had a narrower MF spectrum in the Auto condition. The two types of anxieties may certainly overlap and this finding could be solidified in further testing. Ego resilience showed negative correlation with the measured MF spectrum difference in the Auto and Human conditions. This finding suggests that people with higher levels of ego resilience were not affected as greatly by the two conditions. This finding further indicates that our measures may serve as sources of useful information for future design and marketing purposes.

Frontal alpha asymmetry values were positive in all but two participants in all conditions, suggesting that the overall affectivity was positive or approaching positive during the whole experimental session, and it was slightly more positive in the Human than in the Auto condition. Despite the scarcity of literature on frontal alpha asymmetry related to self-driving vehicles, this pattern is comparable with results of Abdur-Rahim and colleagues [2] who found enhanced right frontal activation when participants drove autonomous wheelchairs through a narrow path. However, in the self-driving mode EEG signals were insufficient to predict stress but GSR signals indicated higher stress levels, probably due the lack of control over the vehicle. In contrast, Seet et al [5] demonstrated decreased alpha power in the right frontal areas when participants had no option to take over the drive of an autonomous car which suggests that participants felt motivated to control the driving. They also speculated that frontal alpha activity might be a neural correlate of trust in autonomous vehicles as it was modulated by the urge to take over control of the vehicle. Despite the fact that no dangerous situations were indicated in the present study, participants were not able to control the car. Therefore, observing the lack of control over the vehicle in the Auto condition could lead to lower alpha asymmetry scores, implying lower trust. This is in line with behavioral results indicating that directly experiencing autonomous technology increased trust, but decreased interest in fully automated driving technology. This phenomenon could be explained by imperfect technology or subject expectations being too high due to media hype [1]. Similarly, in our study, participants may have been disappointed by disallowed from driving the autonomous vehicle. Lower trust was observed in subjects as the vehicle was unable to perform every maneuver (for example full turnabouts) and according to subjects' reports did not drive as smoothly as with a human driver.

Arousal level decreased significantly in the second part of the ride in the Human condition, suggesting that the passenger had become familiarized with the experience. In contrast and unsurprisingly, high arousal level was retained during the whole ride in the Auto condition. The arousal enhancement to the Auto condition conforms to the literature: despite the entirely safe and predictable rides, being passenger in an autonomous car mounted with EEG and eye-tracker could be an exciting experience either in positive or in negative way, leading to enhanced arousal and alertness [42, 39, 3].

The relationship between EEG power spectrum and personality traits can be regarded as exploratory findings, therefore they need to be interpreted cautiously. Frontal alpha asymmetry revealed a negative relationship with Ego-resilience in both conditions. This result suggests that lower approach was related to stronger flexibility and resiliency toward constantly varying situations, and to higher motivation to seek new information in the world [43]. This seemingly contradictory effect might be due to the discrepancy between expectations and experiences of participants as detailed earlier [1]. The negative relationship between frontal alpha asymmetry and Agreeableness might suggest that people with higher agreeableness worry more about self-driving technologies [44]. Arousal values correlated positively with PANAS positive scale change from the beginning to the end of the ride. That is, being passengers in an autonomous car enhanced their overall subjective positive affectivity, and larger arousal was accompanied by stronger positive change. The latter effect was also correlated positively with ratings about the participants' subjective impressions. A marginal positive relationship was found with Agreeableness scores in the Human condition, but in the Auto condition the relationship was significant. This suggests that participants who were more friendly and empathetic exhibited higher arousal in both conditions. The positive correlation between neuroticism, Rotter's locus of control, and arousal measured in Auto condition implies higher arousal levels in more neurotic persons and in individuals with external control. This result is in line with literature on the positive relationship between higher frequency oscillations and neuroticism [45-47] and locus of control and stress [48]. Again, such correlations can easily lead to unproven speculations about self-rated traits and EEG oscillatory activity which [49, 50].

Although the present study was launched as a pilot project, it has numerous strengths. We measured EEG and eye movements simultaneously, which combined with self-report evaluations allowed us to reveal relationships between these three methods. In contrast to the vast majority of studies applying VR or other simulation settings [2-5], the present study was carried out in a real-world environment in an autonomous vehicle. Though measurements could not be conducted in traffic due to safety reasons, simply experiencing the ride can be evaluated as ecologically valid.

There are several limitations of the present study: Firstly, most of our analyses can be regarded as explorational, especially the correlations between biological signals and personality traits – suitable for a pilot study but more systematic and hypothesis-driven testing is needed for more reliable results. Secondly, in order to keep gradual change from the baseline to Human and Auto modes, the order of the conditions was the same for all participants. This order effect can explain for example the decreasing frontal alpha asymmetry to the Auto condition: the motivation or the positive affectivity which was present at the beginning could attenuate to the end of session, especially when participants' expectations of the autonomous technology were not met. In the future, at least the order of the Human and Auto conditions should be balanced. A third weakness was that participants were highly motivated volunteers, which could significantly impact both their neural responses and attitudes.

In summary, the present study demonstrated differences in eye-movement patterns and neural correlates between experiencing human- and self-driven modes of autonomous vehicles. Our preliminary findings suggest that although participants' affectivity was slightly less positive in the autonomous mode, they were more aroused, which is also compatible with personality traits and subjective reports. With respect to the UTAUT2 model, our results clearly indicated that neuropsychological and behavioral data collection and analysis may indeed enhance the predictive power and usefulness of traditional data collection methods. Future studies need to investigate the exact relationship between different factors more systematically. For example, the differences in neural signatures might be useful and promising for exploring neural correlates of trust and acceptance of autonomous vehicles.

Methods

Participants and Procedure

For the present study, 17 healthy adults volunteered (mean age: 29.35 years, SD = 4.24 years, 7 females, 1 left-handed). All of them reported normal or corrected-to-normal vision and hearing and no psychiatric or neurological problems. Participants received no monetary compensation and all of them gave written informed consent. The experiment 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. EPKEB ref. number 2020-89, approved on 07/06/2020 (http://epkeb.ttk.hu/).

Before the experiment, participants were required to fill personality and demographic questionnaires (see below) via an online form. The experiment took place at Szeged Airport (ICAO: LHUD), an airport serving Szeged, a city in Csongrád-Csanád county, Hungary. The airport has one asphalt paved runway designated 16R/34L which measures 1,185 by 30 meters. The runway and a service road leading to the runway were used for the tests. Before the test runs in the vehicle (TESLA Model X) participants were debriefed and both the eye-tracking glasses and the EEG electrodes were mounted. Eye-tracking and EEG data were routed into two separate portable laptop computers. First, a baseline measurement was applied to map participants' reactions to visual stimuli approximately 60-70 cm distance from the display. Twenty-three pictures with different valence and arousal evoking values were selected from the Open Affective Standardized Images Set (OASIS; [51]). Each picture was presented for 5 seconds, followed by a blank black screen for another 5 seconds. Participants were instructed to relax and look freely at pictures without any additional task. Baseline measurement lasted about 4 minutes. After baseline measurement, the participant, the driver and two experimenters with the recording computers entered the vehicle. The participant was seated in the passenger's seat while the two experimenters were seated in the back seat operating the recording equipment. The route was taken twice: first, a professional 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*). Both types of blocks lasted about 2 to 3 minutes and were recorded separately. Before and after the two runs, participants filled out the PANAS scale.

Measures and data analyses

Eye tracking recording. For eye tracking we used the Core System manufactured by Pupil Labs (Berlin, Germany) attached to a portable laptop computer. This system has two cameras: one is positioned forward to record the field of view of the wearer in HD video at 30 Hz, and a second infrared camera recorded the participant's eye movements. Pupil Player, software developed by the manufacturer, was used to determine the movement of the eyes in 3D.

Preprocessing data. The raw data of the time series of the xyz pupil positions were transcoded into a single one-dimensional vector, namely the intensity of the movements without regard to movement directionality. Data recorded at each trial were divided into a first half of the run (before the car took a U turn at the end of the runway) and a second half (after the U turn).

Data analysis. Multifractal analysis of each half run was applied using the Chhabra and Jensen (CJ) method [52]. This is a canonical "direct" algorithm for calculating the multifractal-spectrum width that samples measurement series at progressively larger scales. Empirical examples suggest that the CJ method is suitable for assessing biological movements similar to the movement of the eye. Binomial logistic regression was applied with the MF spectrum width as predictor on the dichotomous variable of the driving condition (human vs autonomous). Psychological survey data was investigated for reliable patterns with the MF spectrum width during every trial.

EEG recording. Continuous EEG data was recorded at a 200 Hz sampling rate with a portable OpenBCI 4-channel Ganglion board utilizing Lab Streaming Layer (LSL) from OpenBCI GUI. Four gold cup electrodes were attached to participants' heads with conductive paste (Ten20) in accordance with the 10-20 system [53] to F3, F4, FPz and Oz. Two additional electrodes were attached to the left and right mastoids serving as reference and ground electrodes, respectively. Impedances were kept below 30 kΩ.

Preprocessing data. The continuous EEG was filtered offline; first, electric line noise was removed by a 50 Hz notch filter. Second, a bandpass filter (7-45 Hz, 9^{th} order Butterworth) was 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 artefacts) were excluded from further analysis. Power spectral densities (PSD) were calculated to alpha (8-12 Hz), beta (13-30 Hz) and gamma (30-45 Hz) band ranges utilizing the Welch method. For each epoch, an index for valence (affectivity) and arousal were computed. Affectivity corresponded to frontal alpha asymmetry and was calculated as difference between $\log_{10}$ transformed values of F4 and F3 with higher values representing more positive emotional valence [37]. As higher frequencies were found to index a more aroused state in frontal areas [40,3], arousal was defined as the ratio of PSD in the beta and gamma range to the alpha range at the averaged F3 and F4 electrodes. As the eye-tracking data, the first and second halves of each condition were also averaged separately.

Statistical analyses. Differences between the first and second parts of the ride as well as the whole blocks were assessed by paired samples t-tests. Spearman's rho correlation coefficients were calculated between valence and arousal values and questionnaires. Statistical analyses were conducted in R (version 3.5.3 [54]). Generalized eta-square (η^2_G) effect sizes were also reported [55, 56].

Questionnaires

Ego-Resiliency Questionnaire (ER89). We used the Hungarian version of the Ego-Resiliency Scale (ER89) including three factors utilizing a 4-point Likert scale: 1) Active engagement with the world, 2) Integrated performance under stress, and 3) Repertoire of problem-solving strategies [43]. Higher scores indicate better problem-solving strategies, better performance under stress, and more active engagement with the world, respectively.

Positive and Negative Affect Schedule (PANAS). The Hungarian version of PANAS was utilized [57]. Negative or positive statements are rated on a 5-point Likert scale. Higher scores represent a higher level of positive or negative affective response.

Brief 30-item Bipolar Rating Scale for the Five Factor Model of Personality (BBRS-30). We used the Brief 30-item Bipolar Rating Scale assessing the following personality traits by a 7-point semantic differential scale: Extraversion, Neuroticism, Conscientiousness, Agreeableness, Openness [58]. Higher scores indicate higher levels of the relevant traits.

Brief Sensation Seeking Scale (SSS). We used the Hungarian version, in which each item contains two choices and the responders have to choose which of the options describes themselves better. Higher scores indicate a higher level of sensation seeking [59, 60].

Spielberger State-Trait Anxiety Inventory(STAI). We used the Hungarian version of the self-report State-Trait Anxiety Inventory. The responders indicate on a 4-point Likert rating scale the frequency at which they experience specific anxiety symptoms at a particular time (state anxiety) or in general (trait anxiety). Higher scores indicate higher anxiety [61].

Rotter's Locus of Control Scale. According to the theory on locus of control [62], people with an internal locus of control believe that the outcomes of their actions are results of their abilities, while people with external locus believe that life events are out of their control and are results of external factors (e.g. fate or luck). We used the Hungarian adaptation consisting of 29 items, and the participants had to select between two statements for each question that they agreed with the most. Lower scores indicate internal control while higher scores indicate external control.

Trolley Dilemma. The trolley problem is a classic series of thought experiments asking about sacrificing a person in order to save several others. Thirteen different trolley dilemma scenarios were created utilizing moralmachine.net (e. g. [63]) and responders had to decide what the self-driving car should do. Here we calculated the percentage of “save passengers"” (i.e. “sacrifice pedestrians”) answers for all of the participants.

Attitudes towards autonomous vehicles. To assess participants’ attitudes towards autonomous vehicles, we translated items of the questionnaire utilized by Charness et al. [64] to Hungarian. Some of the questions were asked in the form of a 5-point Likert scale, while other questions could be answered on a 10-point Likert scale. To get a single score for each participant, we calculated the mean score of their answers. Higher values indicate higher acceptance of self-driving vehicles and indexing greater trust in them.

Declarations

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Competing Interests

The authors declare that they have no competing interests.

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Tables

Table 1 *Summary of survey data*

	Theoretical Minimum	Theoretical Maximum	Minimum	Maximum	Median	Mean	Standard Deviation
TD							
Self-defensive answers %	0	100	0	100	55.56	54.17	31.99
AK							
	1	10	2.68	8.45	6.90	6.53	1.47
Mean score							
STAI (total scores)							
	20	80	23	56	31	32.59	8.46
State anxiety							
	20	80	30	56	37	36.94	6.05
Trait anxiety							
BBRS-30 (mean scores)	1	7	3.33	7.00	5.17	5.17	1.20
Extraversion	1	7	1.17	4.67	2.50	2.73	1.03
Neuroticism	1	7	3.83	6.83	5.83	5.70	0.82
Conscientiousness	1	7	3.33	5.50	4.67	4.59	0.72
Agreeableness	1	7	3.17	6.50	4.33	4.38	1.03
Intellect/Openness							
ER-89	14	56	38	52	45	44.12	4.11
Total score	1	4	2.75	4.00	3.25	3.26	0.36
RPSS mean score	1	4	1.00	4.00	3.00	2.85	0.79
IPUS mean score	1	4	1.80	4.00	3.20	3.14	0.61
AEEWW mean score							
	0	23	2	14	9	8.41	3.54
LOC							
Total score							
	0	7	0	7	4	3.29	2.26
SSS							
Total score							
	10	50	30	48	40	40.24	4.82
PANAS – before SDE	10	50	9	16	10	11,06	2,08
Positive affect Score							
	10	50	25	50	42	41.47	6.32
Negative affect score	10	50	10	15	10	10.59	1.33
PANAS – after SDE							
Positive affect Score							

Negative affect score	

Notes. **TD** – The Trolley Dilemma. Scores indicate the percentage of answers that could be categorized as „save self" rather than „save others". **AK** – Attitudes towards autonomous vehicles. Higher scores indicate higher acceptance of and trust in self-driving vehicles. **STAI** - Spielberger State-Trait Anxiety Inventory. Higher scores on the subscales indicate higher anxiety. **BBRS-30** - Brief 30-item Bipolar Rating Scale for the Five Factor Model of Personality. Higher scores indicate higher levels of extraversion (thus lower introversion), higher levels of neutroticism (thus lower emotional stability), higher levels of conscientiousness, agreeableness and intellect/openness respectively. **ER-89** – Ego Resiliency Questionnaire (ER-89). RPSS: Repertoire of (cognitive, social and personal) problem solving strategies. IPUS: Integrated performance under stress. AEWW: Active engagement with the world. Higher scores indicate better problem solving strategies, better performance under stress, and more active engagement with the world, respectively. **LOC** – Rotter's Locus of Control Scale. Lower scores indicate internal control, higher scores indicate external control. **SSS** – Brief Sensation Seeking Scale. High scores indicate sensation seeking behaviours. **PANAS** - Positive and Negative Affect Schedule. The test was administered twice, before and after the self-driving experience (SDE). Higher scores indicate a higher level of affective response (negative or positive). One of the participants didn't answer to one question, hence the minimum score that is lower than the theoretical minimum on the test.

Figures

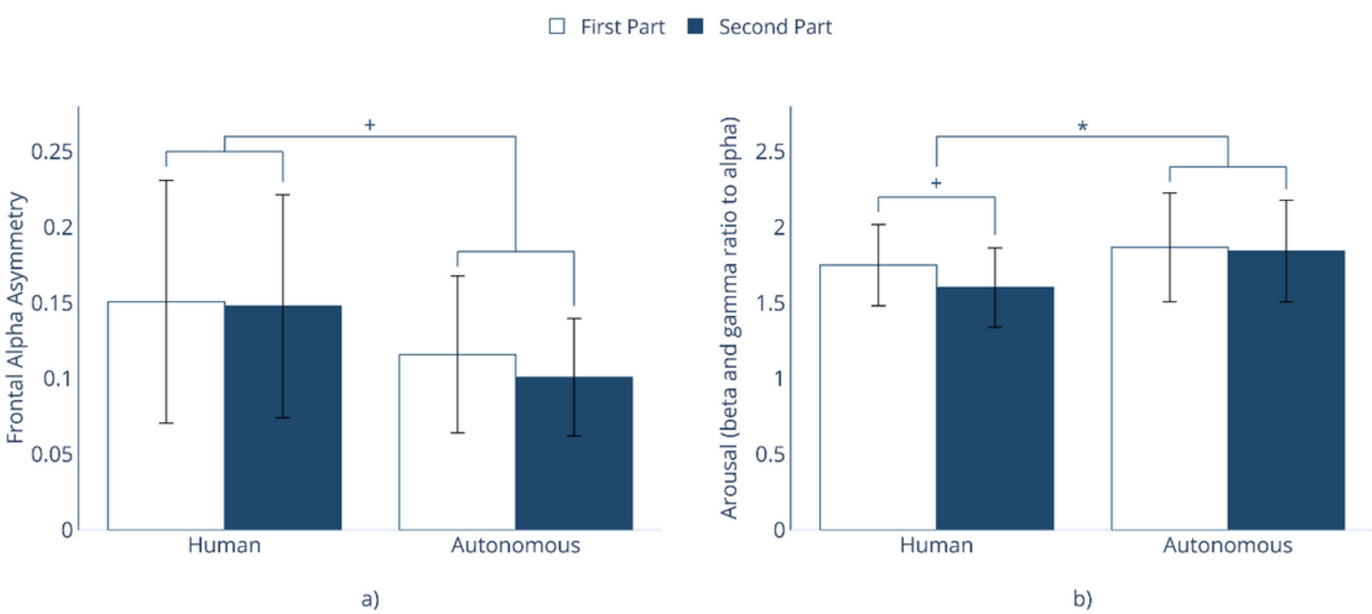

Figure 1

EEG correlates of passengers' experience in the autonomous vehicle. White bars denote the first part and blue bars denote the second part of the ride in the Human and Autonomous condition. Participants were characterized with frontal alpha asymmetry (a) and arousal (b) scores. Whiskers indicate the 95% CI; star sign denotes significant ($p < 0.05$) differences and plus sign denotes marginally significant ($p < 0.1$) contrasts.