Original Research

Neurological Measurement of Human Trust in Automation Using Electroencephalogram

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Abstract

In modern society, automation is complex enough to perform advanced tasks. The role of the human operator to control and monitor complex automations is crucial to avoid failure, to reduce risk, and to prevent unpredictable situations. Measuring the human operators' level of trust is crucial in predicting their acceptance and reliance on the automation. This research used an electroencephalogram (EEG) as a neurological measure to identify specific brainwaves in situations of trust and mistrust in automation. Power spectrum analysis was used for brainwave analysis. The results indicate that the power of alpha and beta waves was stronger for the trust situation; whereas, the power of gamma waves was stronger for the mistrust situation. When the level of human trust in automation increases, the use of an automatic control increases. Therefore, the findings of this research will contribute to defining how trust in automation affects the human operator's monitoring, decision-making, and overall performance.

Keywords- Trust; mistrust; automation; electroencephalogram (EEG), power spectrum

INTRODUCTION

Automation is the use of various controls to operate equipment with minimal or reduced human intervention. To consistently improve quality, accuracy, productivity, and efficiency, automation is actively used in many applications (e.g. machinery, factories, ships, aircraft, and vehicles). Automation can replace humans in tasks that involve physically strenuous and monotonous work, can improve safety in dangerous and hazardous environments, as well as reduce human labor costs and expenses. In addition, automation is used to reduce human errors in repetitive or complex mass production. Automation evolved very rapidly into complex, sophisticated tasks and advanced technology. Trust can play an important factor in 'decision aid' when dynamic and uncertain situations in complex automated systems are impossible to comprehend, and when flexible behaviors are necessary to combat unexpected situations that arise, which are unavoidable using procedures [24]. Trust also plays a crucial role in contributing to the cognitive complexity and increased uncertainty in sophisticated automated systems.

To understand trust between humans and automation, it is necessary to define trust. Trust has been defined as being related to expectation. Deutsch [9] defined trust as "confidence that one will find what it desires from another," and Rempel *et al.* [36] defined it as "a generalized expectation related to the subjective probability" to future events. A sociologist Barber [2] defined trust with three specific expectations: persistence, technical competence, and fiduciary responsibilities. Muir [30] integrated and extended the studies of [2, 36] to define trust in human-machine relationships and claimed that trust is developed by "the human's ability to estimate the predictability of the machine's behaviors" which is adopted in this research.

Trust between humans and automated machines is similar. Trust is developed over time but is very hard to regain once gone. Humans (trustor) can develop trust in a machine (trustee) by evaluating the performances of the machine over time. With trust, the human is willing to rely on the use of the machine. If the machine's outcome is unexpected and unstable, increasing the risk of failure or harm to humans, humans will lose their trust and not rely on the machine in the future. Several researchers investigated factors that influence the use of automation and found that trust is an important factor that affects misuse and disuse of automation [4, 23, 24, 30]. Trust is a variable in deciding to use automation [27]. Therefore, the key here is maintaining a level of trust in the interaction between humans and automated machines.

Measuring the human operator's level of trust in automation is crucial in predicting their strategies while using automation. However, trust is a multidimensional construct influenced by various factors, such as motives, intentions, and actions [3, 28], so it is challenging to measure trust. How can we measure human trust in the use of automation effectively? As a method to measure trust, questionnaires are mostly used to investigate trust in interpersonal relationships [22, 36], and have been used with an empirical approach [5, 17], and with a semi-automatic simulation of human and automation [23]. The questionnaires used in these studies are based on a theoretical or empirical approach, which can vary by the researcher's respective theoretical orientation or specific model of simulations. Therefore, this research used both a neurological measure as a quantitative method and a questionnaire as a qualitative method to examine responses of human trust in automation. Neurological measure can be a direct and objective method to detect and measure human trust.

Some studies have investigated the relationship between social constructs (i.e., trust) and neural or physiological evidence. Winston *et al* [44] used event-related functional magnetic resonance imaging (efMRI) to examine the correlation between trust and human facial expression. They found that trustworthiness was correlated in a frontopolar cortex, and untrustworthiness was correlated with the right amygdala and right insula. Dimoka [10] found a correlation between brain regions and trust using functional magnetic resonance imaging (fMRI) to measure the responses of participants toward two fictitious online sellers who had high and low reputations. They found that trust is related to the caudate nucleus, putamen, anterior paracingulate cortex, and orbitofrontal cortex, while distrust is related to the amygdala and insular cortex. Casado-Aranda *et al*. [6] examined online trust signals using fMRI. They found seals of approval relate to trust, because they activate brain regions dealing with reward, however, rating systems relate to mistrust, because they activate brain regions dealing with risk and negativity.

These previous studies utilized fMRI and efMRI to analyze brain regions, which were found to engage with stimuli related to trust and distrust. Other studies used an electroencephalogram (EEG) in examining factors that can affect human trust and decision-making [11, 12, 14, 21]. Findings showed neurological correlations between a user's surprise, frustration, workload, and level of trust in the human-computer interaction using functional-near-infrared spectroscopy (fNIRS) and electroencephalography (EEG) [14]. Dong *et al*. [11] measured through EEG human trust in machines depending on participants' technical capability through a collaborative and egoistic theory-of-mind game. They found that neurological activities are affected by humanlike cues, which depended on their partner's technical capability of detecting different event-related potential (ERP) patterns. Ferrez and Millan [12] investigated new error-related potentials (ErrP) with slow cortical potential in the EEG in human-computer interactions developed from the ErrP when people were aware of their errors. Kumar *et al*. [21] reviewed error-related potential (ErrP) based brain-computer interfaces (BCIs) from an aspect of assisting people with mobility impairment. However, the previous studies have not identified specific brainwaves in the situations of trust and mistrust in automation, which will help researchers understand how humans trust automation or machines.

This research identifies specific brainwaves in situations of trust and mistrust in automation using an electroencephalogram (EEG). An EEG was selected due to its benefits over MRI for measuring brain activity. One benefit is that an EEG can sensitively detect changes in the brain's electrical activity in response to external stimuli in various brain regions within a millisecond. Therefore, EEG is useful for experiments with a wide range of cognitive tasks and real-world applications in the future. The EEG records signals on the scalp and therefore has a few limitations. One limitation is that this technique cannot measure deep brain areas directly. Another is that the EEG is sensitive to various noises other than the stimuli, causing it to pick up facial movements such as an eye blink, jaw clenching and muscle movement. The researcher acknowledges these limitations and has made the following provisions such as marking and removing artifacts from the raw data before analysis.

Despite the limitations of EEG, there are numerous benefits associated with using EEG to measure human trust in this research. Research supports EEG as an appropriate way to measure neurological active responses to stimulus involving trust and mistrust in real time [25]. Even though previous studies using fMRI and efMRI have shown the stimulated brain regions relating to trust and mistrust and other social constructs, this study aims to refute or validate previous research studies. This study is unique from most other research studies because there are only a few studies [42] that used EEG to investigate correlations between specific brainwaves and human trust.

Trust in automation will increase the use of automaton and mistrust in automation will decrease the use of automation. Findings from this research will contribute to defining how trust in automation can affect the human operator's decision-making and overall performance. This research discovers correlations between neurological activities and trust and mistrust situations. Through this correlation, we identify specific brainwaves associated with situations of trust and mistrust using an EEG. This research is unique to previous literature because this neurological method (EEG) provides a direct and objective way to detect and measure human trust and mistrust toward any assigned task in real time. To investigate the multidimensional concept of trust, this research examines neurological activities of trust and mistrust, which are unconscious and hidden, and utilizes supplementing questionnaires with a subjective rating. Second, this research can be beneficial in designing automated systems, which require gaining the trust of human operators to achieve maximum performance and safety.

Automated systems have become complex enough to execute high level tasks; thus, these systems have become difficult to fully understand, properly use, and critical for human operators to monitor. By detecting human operator's trust in automation, designers can improve automated systems by developing user-friendly interfaces and effective training programs, which can decrease workload and increase trust. Further, this research can be a means of monitoring the psychological state of the human operators. Human operators monitor the automated systems to avoid failure and malfunction. The human operators can report their ability to operate the automatic system properly; however, there are no systems or programs to monitor the human operators. This EEG method can monitor the human operator and detect the human operator's trust in automation. If the EEG shows the human operator mistrusts automation, training or improving the automated system are ways to regain trust. If the EEG shows the human operator is unstable and unfocused due to extreme stress and anxiety, operating in full automation rather than manual operation is recommended, especially in emergency situations.

MATERIALS AND METHODS

- *Participants*

A total of 28 volunteers participated in this experiment. The participants were undergraduate and graduate students recruited at the NC A&T State University. Each subject was over 18 years old with normal or corrected-to-normal vision, was free of current or past neurological and psychiatric disorders, and was able to read and comprehend the English language. There was no preference on right-handed or left-handed users, but all participants must have had the ability to use a keyboard and a mouse with their hands. The subjects read and signed an informed consent agreement before the experiment.

- *EEG Recording*

The EEG data was recorded using a g. HIamp (256 multichannel amplifier), g. GAMMAsys (active electrode system with g. GAMMAcap), and g. Recorder (brain signal recording software) by g. tec medical engineering company. The 20 electrodes (Fp1, Fp2, Fpz, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, T6, O1, O2) were placed and recorded according to the international 10-20 system of electrode placement (see Figure 1). The subject's head was fitted with a cap of electrodes (g. GAMMAcap) and the selected 20 electrodes were filled with abrasive electrolyte gel using a syringe. The settings to record the brainwaves were as follows: the sampling frequency was set at 256 Hz, the high frequency filter at 60 Hz, and the low frequency filter at 0.1 Hz.

Before each experiment began, participants' brainwaves were recorded in order to identify artifacts to mark and remove later, such as eye blinking, jaw clenching, and muscle movement. Then, as baseline data without any stimuli, participants' brainwaves were recorded when they were relaxed. During this time, they were instructed not to move, not to talk, and to watch the blank monitor for a minute. When the experiment began, the participant was asked to focus their attention on the computer screen and use the keyboard or mouse if needed. They were asked not to talk or blink their eyes (if possible) to reduce recording artifacts in the brainwaves. This experiment was proved with IRB 17-0159.

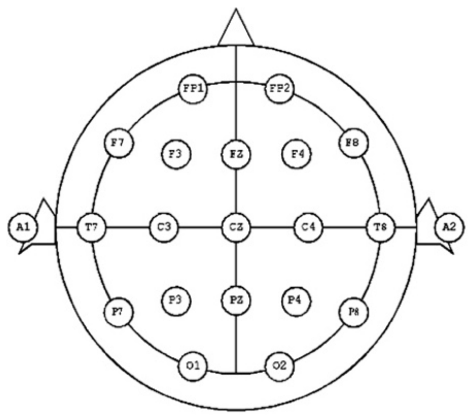


FIGURE 1
INTERNATIONAL 10-20 SYSTEM FOR ELECTRODE PLACEMENT [20]

- *Experiment*

To investigate trust between humans and automation, an experiment was designed to measure neurological activities of decision-making during automatic or manual control and to record the participants' use of automatic control. This experiment used a simulated driving game with 10 trials related to decision-making and a survey after the experiment. This experiment was designed to change the human-automation relationship from trust to mistrust by having the participants detect fault of automation from low performance.

The experiment required each participant to become a human operator that controlled a simulated driving experience in the format of an interactive game using a keyboard and a mouse. The simulated driving game consisted of training sessions and 10 trials (see Table 1). Before operating each simulated driving period, the participant chose between automatic or manual control of the movement of the vehicle. The participants' brainwaves were recorded during each trial, including the decision-making process and simulated driving period. However, only the brainwaves that were associated with decision-making (automatic or manual control) were analyzed.

All 28 participants individually participated in the training session and the 10 trials of the simulated driving (see Table 1). After the 10 trials, participants were given a survey to evaluate the level of trust between people and automation with 7 scales (see Appendix A). All participants completed the training session by practicing both the auto and manual control for 6 trials. The purpose of the training session was to familiarize participants with the interface of the game and to develop trust in the automatic control by proving a 100% performance rate. After the training session and break, each participant began operating by choosing either automatic or manual control at the beginning of each trial to achieve a high-performance rate by avoiding over 25 cars. After their decision of control, he or she could not change their choice during the simulated driving. During each trial, the screen displayed a performance rate with a score that showed how many cars were avoided (see Figure 2).

TABLE 1
EXPERIMENT DESIGN

Trials	Training	Break	T1	T2	T3	T3	T4	T5	T6	T7	T8	T9	T10
Performance Auto (%)	100		100	100	100	100	100	100	32	20	16	36	32

FIGURE 2
EXAMPLE OF THE SIMULATED DRIVING

As a human operator, each participant was given a performance goal to avoid over 25 cars from the opposite direction without any accident. Performance was measured as the number of cars avoided before the accident. Successfully avoiding over 25 cars resulted in a 100% performance rate, while avoiding just 1 car resulted in a 4% performance rate. The previous performance affected the participants next decision to choose between an automatic or manual control. For the human operators that decided to use automatic control, Trials 1 to 5 were designed for the participant to develop trust in the automatic control by showing consistent and reliable performance (at a 100% performance rate). Trials 6 through 10 were designed for the participant to develop mistrust in automatic control by low performance (below the 40% performance rate). In order to avoid interruption and noise in recording brainwaves, there was no break between all 10 trials.

- *EEG Analysis*

EEG provides a visual representation of brain waves as complex patterns of electrical signals; therefore, there is no value in analyzing the raw data directly. The *g.Recorder* (brain signal recording software) recorded raw EEG data and removed artifacts through filtering. Before an experiment, participants' artifacts, such as eye blinking, jaw clenching, and muscle movement, were recorded and marked. After the experiment and before the analysis, the marked artifacts were removed from raw data using the filters in *g.Recorder*.

For analysis, power spectral density (PSD) was utilized, because it is a reliable and fast method to define specific brainwaves (i.e., alpha, beta, and gamma waves), which were analyzed in the frequency domain to evaluate the situation of trust and mistrust. The power spectrum measurement is a common method to quantify EEG raw data to illustrate the distribution of signal power by frequency [39]. After the artifacts were removed, the EEG data was analyzed using the power spectrum analysis through the *EMSE Suite Data Editor* (EEG data editing software) by *Cortech Solutions.* With the power spectrum analysis, brain waves can be classified by frequency ranges: delta waves (0.2-4 Hz), theta waves (4-8 Hz), alpha waves (8-13 Hz), beta waves (13-30 Hz), and gamma waves (30-60 Hz). This experiment analyzed only alpha, beta, and gamma waves, which are related to decision-making.

RESULTS

- *The rate of automatic control and the trust level*

All 28 participants completed 10 trials by choosing the automatic or manual control for each trial. For trials 1 to 6, the level of trust increased from 57% to 94% whereas using the automatic control increased from 79% to 96% (see Figure 3). On the other hand, when an error of automatic control with 32% of performance rate in trial 6, trial 7 showed a substantial decrease in the level of trust from 94% to 30%, and a decrease in the automatic control from 96% to 21% (see Figure 3). These results imply that when the trust level in automation increases, the use of an automatic control will increase.

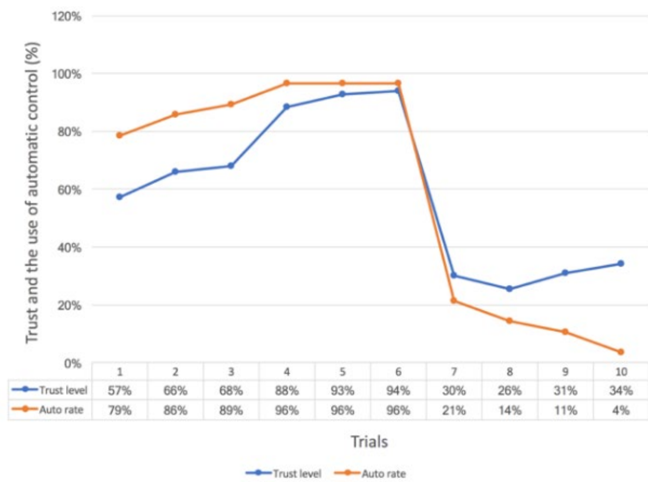


FIGURE 3
COMPARISON OF THE TRUST LEVEL AND THE USE OF AN AUTOMATIC CONTROL

- *Comparisons of intraindividual and average differences*

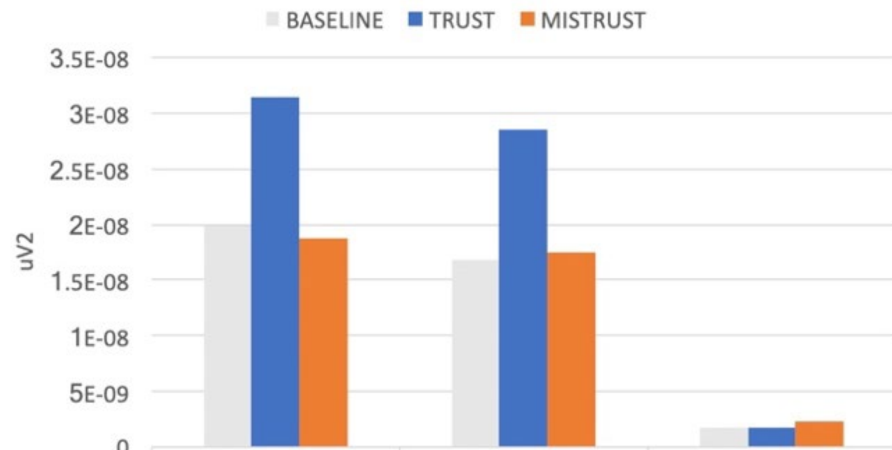
The frequency of alpha waves ranged from 8 Hz to 13 Hz. By comparing the intraindividual differences between the trust situation and the baseline (with no stimuli), the power of alpha waves of 27 of 28 participants (96.43%) highly increased, but the power of 1 participant (P16) (3.57%) decreased (see Figure 5). By comparing the intraindividual differences in the mistrust situation to the baseline (with no stimuli), the power the alpha waves of 26 of 28 participants (92.85%) slightly decreased, but the power of 2 participants (P5 and P24) (7.14%) increased (see a in Figure 5).

The frequency of beta waves ranged from 13 Hz to 30 Hz. The comparison of the intraindividual differences of the trust situations to the baseline (with no stimuli) showed the power of beta waves for the all 28 participants (100%) increased considerably (see Figure 5). Contrarily, the comparison of the intraindividual differences for the mistrust situations to the baseline (with no stimuli) showed the power of the beta waves for 26 of 28 participants (92.85%) increased slightly, but the power of 2 participants (P3 and P16) (7.14%) decreased (see b in Figure 5).

The frequency of gamma waves ranged from 30 Hz to 60 Hz. The comparison of the intraindividual differences for the trust situation to the baseline (with no stimuli) showed the power of the gamma waves decreased slightly for the 22 of 28 (78.57%) participants, but 5 participants (P6, P14, P16, P26 and P27) (17.85%) increased and 1 participant (P4) (3.57%) didn't change (see Figure 5). The comparison of the intraindividual differences for the mistrust situation to the baseline (with no stimuli) showed the power of the gamma waves increased significantly for the 27 of 28 participants (96.42%), but not for 1 participant (P23) (3.57%) (see c in Figure 5).

The average differences of the baseline, trust, and mistrust of alpha waves are 1.98E-08 uV^2, 3.14E-08 $uV^2$and 1.87E-08uV^2, respectively. A comparison of these averages showed an increase of the power of alpha for the trust situation with a difference of 1.16E-08 uV^2 and a slight decrease in the mistrust situation with a difference of 1.10E-09 uV^2 (see Figure 4). The average differences of the baseline, trust, and mistrust of beta waves are 1.68E-08 uV^2, 2.85E-08 $uV^2$and 1.75E-08uV^2, respectively. A comparison of the average differences showed an increase of the power of beta waves for the trust situation with a difference of 1.17E-08 uV^2 and a slight increase in the mistrust situation with a difference of 7.00E-10 uV^2 (see Figure 4).

The average differences of baseline, trust, and mistrust of gamma waves were 1.75E-09 uV^2, 1.68E-09 uV^2, and 2.25E-09uV^2 , respectively. The comparison of these average differences showed the power of gamma waves increased for the mistrust situation with a difference of 5.00 E-10 uV^2 and slightly decreased for the trust situation with a difference of 7.00E-11 uV^2 (see Figure 4). According to the results of comparisons of intraindividual and average differences, the power of alpha and beta waves was increased in the trust situation, while the power of gamma waves was increased in the mistrust situation.



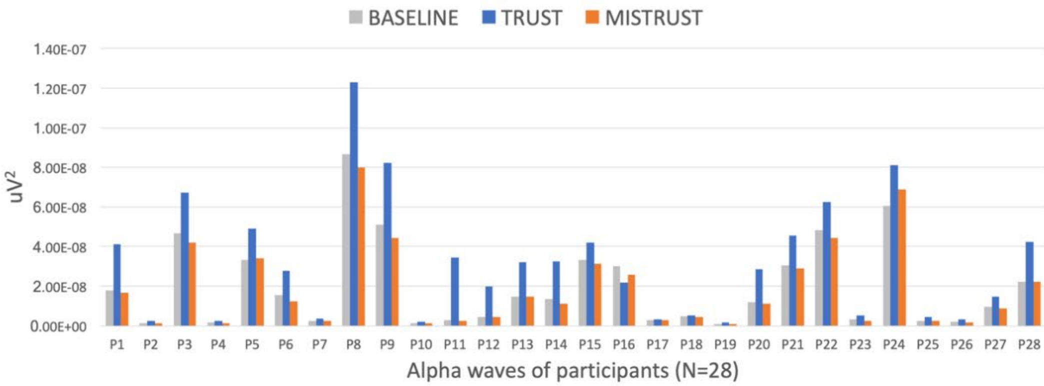
	Alpha waves	Beta waves	Gamma waves
BASELINE	1.98E-08	1.68E-08	1.75E-09
TRUST	3.14E-08	2.85E-08	1.68E-09
MISTRUST	1.87E-08	1.75E-08	2.25E-09

FIGURE 4
COMPARISON OF AVERAGE DIFFERENCE OF ALPHA, BETA AND GAMMA WAVES

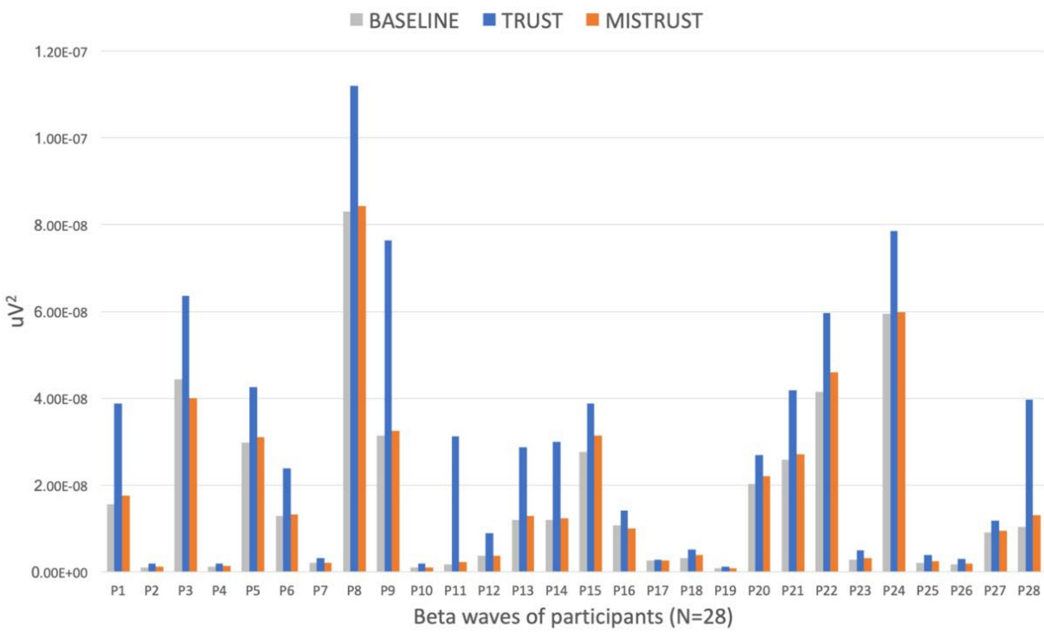
- *Comparisons of trust and mistrust differences*

By comparing the alpha waves, beta waves and gamma waves in human trust and mistrust in automation, the alpha and beta waves are associated with the trust situation and the gamma waves are associated with the mistrust situation, so they need to analyze with more details.

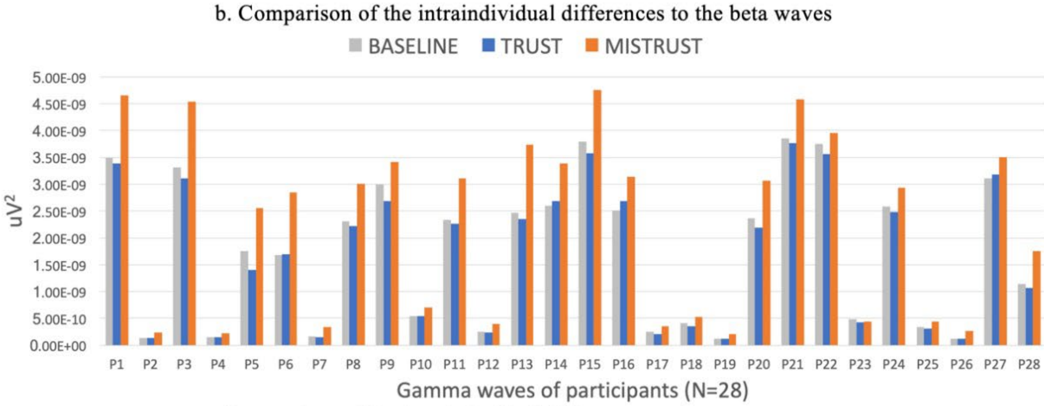
By comparing the trust differences to the alpha waves when the baseline is 0, 96.42% of participants increases in the trust situation and the standard deviation is 1.13E-08E (see a in Figure 6). By comparing the trust differences to the beta waves when the baseline is 0, 100% of participants increases in the trust situation and the standard deviation is 1.18E-08E (see b in Figure 10). By comparing the mistrust differences to the gamma waves when the baseline is 0, 96.42% of participants increases in the mistrust situation and the standard deviation is 4.08E-10E (see c in Figure 6). According to the comparisons of trust and mistrust differences, the alpha and beta waves are increased in the trust situation, while the gamma waves are increased in the mistrust situation.



a. Comparison of the intraindividual differences to the alpha waves



b. Comparison of the intraindividual differences to the beta waves



c. Comparison of the intraindividual differences to the gamma waves

FIGURE 5
COMPARISONS OF THE INTRAINDIVIDUAL DIFFERENCES TO THE ALPHA (A), BETA (B), AND GAMMA (C) WAVES

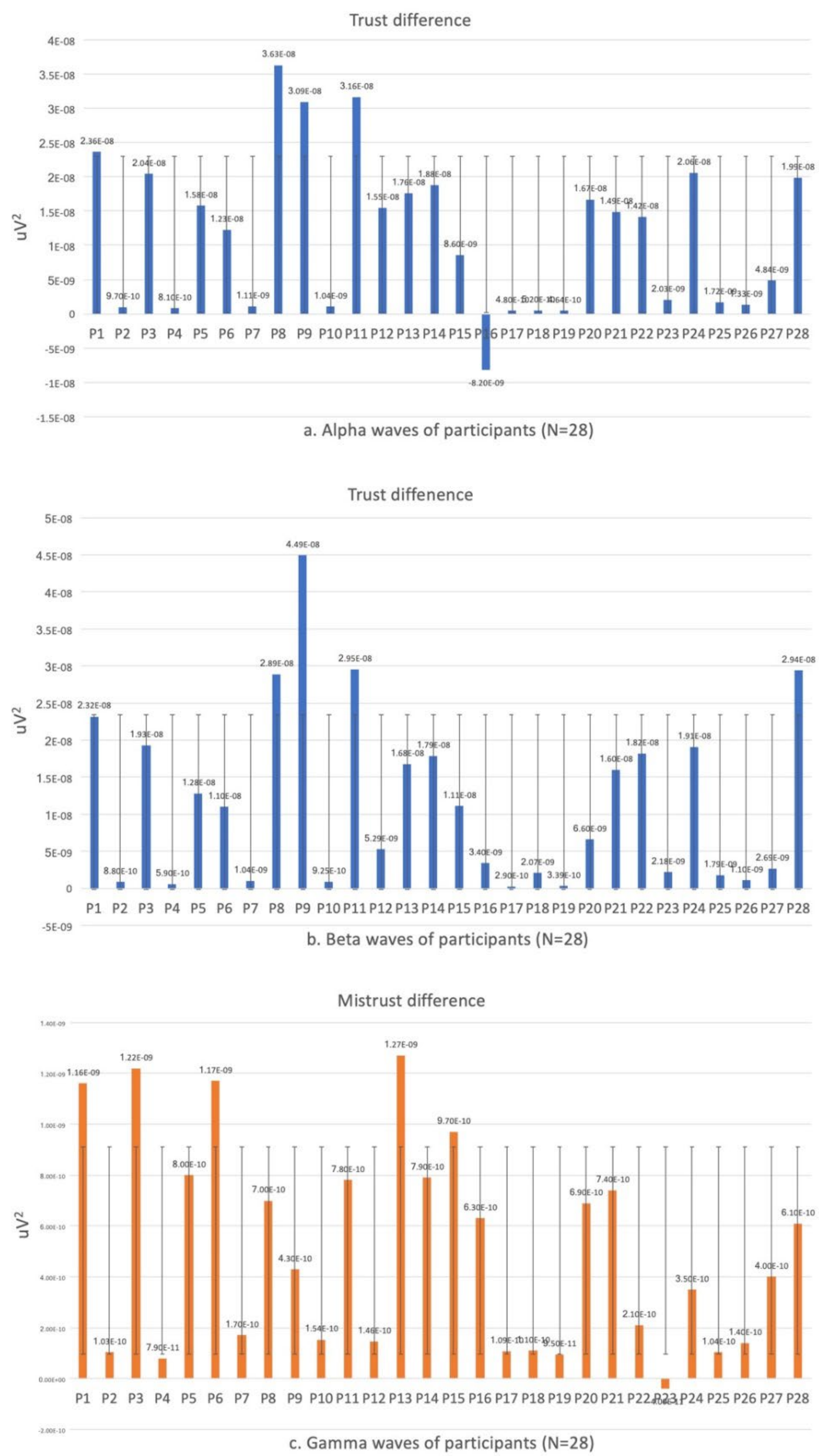


FIGURE 6
COMPARISONS OF THE TRUST AND MISTRUST DIFFERENCES TO THE ALPHA (A), BETA (B), AND GAMMA (C) WAVES

DISCUSSION

According to the results of the experiment with the driving simulation, the power of alpha and beta waves was stronger for the trust situation; whereas, the power of gamma waves was stronger for the mistrust situation (see Figures 4 through 6). The discussion section investigates the neurological relationships that are grounded in the neuroscience literature, which is necessary to understand the relation of alpha, beta, and gamma waves to trust. Alpha waves appear when people are awake but have a relaxed awareness and inattention without processing much information. When people are more comfortable and relaxed, the alpha waves increase. They emerge with the closing of the eyes and with release of tension, and they are suppressed during eye opening or mental exertion. Alpha waves are associated with meditation [34, 38] and reducing stress and anxiety [31, 35, 41, 43]. Beta waves are associated with conscious activities and can be a guideline for measuring the cognitive process [15, 33]. Beta activity is important because it can enhance concentration, attention, emotional stability, and energy levels [1, 26]. Gamma waves are the fastest waves, indicative of anxiety, and process advanced cognitive information, such as reasoning and judgment [18, 19]. Gamma waves can be used to assess the level of psychosocial stress in the prefrontal region [29]. By understanding brain waves, alpha and beta waves in the trust situations were related to normal cognitive process indicating reduced stress and anxiety. However, gamma waves in the mistrust situations are related to complex cognitive process by increased stress and anxiety.

In addition, the results suggested that the specific brainwaves (i.e., alpha and beta waves for trust, and gamma waves for mistrust) for human trust in automation aligns with existing neuroimaging literature that used an Electroencephalography (EEG). Gianotti et al. [13] using EEG found that the decision-making process regarding risk can stimulate neurological activities in the right prefrontal cortex, which is related to an individual's risk-taking behavior. Ota *et al*. [32] investigated the function of the dorsolateral prefrontal cortex (DLPEC) in motor decision-making under risk using EEG. Sacré *et al*. [37] used stereo-electroencephalography (SEEG) to examine risk-taking bias during decision-making and found high-frequency activity in the right hemisphere during high risk decision-making. Risk-taking behavior can also be associated with human operator's strategies when using automation because an individual who has greater risk-taking behavior will tend to over trust and overuse automation even though the operator recognizes an error or fault with automation. Cohen *et al*. [8] used EEG to investigate feedback anticipation and feedback processing using a competitive decision-making game. They found that feedback processing affects increased cross-trial phase coherence and feedback anticipation affected the lower power delta and theta waves and the higher power alpha and beta waves. A study by Cohen and Donner [7] used EEG to investigate conflict processing in decision-making by examining neural oscillation in the medial prefrontal regions, which are related to monitoring conflict and activities involving a goal. Their study showed that theta-band oscillations in the medial frontal cortex is time-locked and not phase-locked to stimuli that responds to conflict in a specific condition.

Previous studies dealt with factors that affect human trust and decision-making using EEG, which support the results of this research. However, few studies identified specific brainwaves associated with trust and mistrust situations that can validate or refute the results of this research. Therefore, additional research is essential to investigate the level of human trust in automation and decision-making.

CONCLUSION

This research investigated human trust in automation using EEG by recording, identifying, and analyzing specific brainwaves in situations involving trust and mistrust. It was discovered how human trust affects the human operator's strategy on the use of automation. By investigating neurological activities of brain waves, the trust situations are associated with alpha waves, which can help to calm down any mental activity without any stress and tension, and with beta waves, which increase attention and help problem solving and decision-making. The mistrust situations are associated with gamma waves, which can interrupt mental activity because of increased stress and anxiety. In addition, when the level of human trust in automation increases, the use of an automatic control increases.

This research measured the multidimensional concept of trust by using both questionnaires (qualitative method) and neuro imaging technique (quantitative method) that identified specific brainwaves associated with human trust in automation. By examining neurological activities of trust in automation, findings of this research can contribute to defining how trust in automation affect the human operator's decision-making and overall performance. This research can be valuable in designing automated systems to develop a user-friendly interface and effective training, which can increase human operator's trust and decrease workload. Further, this research can be applied to monitor the psychological state of human operators in complex automation such as pilots operating automated aircrafts or captains operating automated ships. A neurological measure such as an EEG can monitor and detect the human operator's trust in automation. If human operators mistrust automation, training or improving the automated systems can aid in regaining their trust. If the human operator is not stable enough to operate automation because of extreme stress and anxiety, the recommendation is to use full automation rather than manual operation in urgent situations.

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Appendix A.

Scales for Trust between People and Automation

Below is a survey to evaluate the level of trust between people and automation for each trial. There are scales for you to rate the level of trust of the automatic system when you choose automatic or manual control before operation. Please check the level of trust for each trial.

Record sheet of your decision for each trial (Note: A = Automatic control, M = Manual control)

	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
A or M										

Question: I can trust the automatic system (Note: not at all = 1, extremely = 7)

	1	2	3	4	5	6	7
Trial 1							

	1	2	3	4	5	6	7
Trial 2							

	1	2	3	4	5	6	7
Trial 3							

	1	2	3	4	5	6	7
Trial 4							

	1	2	3	4	5	6	7
Trial 5							

	1	2	3	4	5	6	7
Trial 6							

	1	2	3	4	5	6	7
Trial 7							

	1	2	3	4	5	6	7
Trial 8							

	1	2	3	4	5	6	7
Trial 9							

	1	2	3	4	5	6	7
Trial 10							