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TOPOGRAPHIC MAPS OF BRAIN REGIONS TO MEASURE HUMAN TRUST IN AUTOMATION

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As complex automation increasingly enters the workplace, a human operator's trust affects the proper use of automation. This research aimed to identify stimulated brain regions using topographic maps to measure human trust in automation. Power spectrum analysis classified the frequency range, and coherence analysis identified functional connectivity within the brain regions. The results showed that the frontal lobe in the alpha and beta waves had strong connectivity in the trust situation. In contrast, the temporal lobe in the gamma waves had strong connectivity in the mistrust situation. These findings can contribute to monitoring human operators' trust in automation in uncertain or urgent situations and designing complex automation by calibrating human trust consistent with the automation abilities in the industry.

Keywords: Trust; Automation; Power Spectrum; Coherence; Topographic Maps; Brain Regions

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1. INTRODUCTION

Recent advancements in technology have accelerated automation use in the workplace. Automation can increase productivity, performance, and safety and reduce workload, time, and costs (Meddeb, 2023). However, despite the potential benefits of automation, it is often misused, disused, or even abused. This is because automation is influenced by various complicated factors, including workload, cognitive overload, trust, confidence, and risk (Lee, 2008). Trust in complex automation significantly influences human operators' decision-making and problem-solving in uncertain or unexpected situations. Misuse occurs when operators trust automation inappropriately, leading to automation bias or monitoring failures (Parasuraman and Riley, 1997). Overtrust in automation can reduce operators' attention in evaluating information and situations (Skitka *et al.*, 2000). Failures in monitoring are particularly concerning, as ignoring or missing automation malfunctions can lead to serious consequences. Furthermore, automation abuse refers to the improper deployment of automation by designers who fail to account for its effects on human performance and authority (Parasuraman and Riley, 1997). This issue arises when automation is given excessive control and independence, ignoring the role of human operators (Sarter and Woods, 1994).

Trust plays an essential role in determining the success of human-automation interactions in the workplace. For good performance in the workplace, Seong and Bisantz (2008) stressed the importance of calibrating human trust in the machine using automation. Calibration is needed between trust in automation and the automation's capabilities (Tenhundfeld *et al.*, 2019). When human operators overtrust automation, their level of trust exceeds the actual capabilities of the automation. When human operators distrust automation, their level of trust is lower than the actual automation capabilities. Both over-trust and mistrust can negatively impact workplace performance by reducing the efficiency and safety of operations. The

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degree of trust can influence system performance because it can affect the operator's acceptance degree and reliance on automation (Chiou and Lee, 2023). Poor calibrations can happen in situations of over-trust, leading to misuse or mistrust and disuse (Lee and See, 2004). Good calibration means that the level of trust corresponds to the actual automation capabilities (Lee and See, 2004). Therefore, in the interaction between humans and automation, measuring the human operator's level of trust in automation is essential to predict the operator's strategy in automation use (Muir and Moray, 1996).

Questionnaires are commonly used to measure trust because they allow for examining various aspects of trust as a multidimensional concept through a set of questions. This approach can be theoretical (Holthausen *et al*., 2020), empirical (Jian *et al*., 2000), or based on simulations of humans and automation (Lee *et al*., 2021). Neurological imaging techniques can quantitatively measure trust by investigating neurological activities. Because trust is a complex and multidimensional concept, several studies have attempted to examine factors affecting human trust and decision-making. Dong *et al*. (2015) utilized EEG to measure human trust between humans and machines through a collaborative and egoistic theory-of-mind game. It was accomplished by comparing neural activities associated with different event-related potential (ERP) patterns of brainwaves. A worker's trust can be measured in real-time in human-robot interaction (HRI) using EEG (Shayesteh *et al*., 2022). Using functional near-infrared spectroscopy (fNIRS) and EEG, Hirshfield *et al*. (2011) measured frustration, surprise, and workload, depicting correlations with the level of trust in human-computer interactions (HCI). Winston *et al*. (2013) employed event-related functional magnetic resonance imaging (efMRI) to examine specific brain regions affected by human trust based on facial appearance.

Additionally, another study investigated the brain regions associated with conditional and unconditional trust using event-related hyper-fMRI. This study used an electroencephalogram (EEG) to measure trust in automation effectively to identify specific brain regions associated with trust and mistrust. The fMRI and efMRI are effective neurological tools for detecting brain regions, but participants must lie in large equipment. EEG can be valuable for measuring real-time neurological activities involving trust and mistrust in decision-making (Hu *et al*., 2016). However, EEG is highly sensitive to noise (Xie and Oniga, 2020), so the authors marked and removed noise from raw data using a filter to minimize the disadvantage of the EEG.

Oh *et al*. (2020) used a simulated driving game in trust and mistrust situations. This section provides a detailed comparison of our research and their previous study. Despite the similarity in the simulated driving games used in both studies, the experimental designs and purposes differ. Oh *et al*. (2020) examined the effects of trust and mistrust on specific brainwaves (i.e., alpha, beta, and gamma) using intraindividual differences. It recorded 20 electrodes, followed by the 10–20 system, and analyzed the data collected from the entire brain using a power spectrum analysis. Their study included 28 participants (14 males and 14 females). Based on the results of the ten trials, the brainwaves of trial six were analyzed as the highest trust level, and the brainwaves of trial eight were analyzed as the lowest trust level for all participants.

Unlike the previous study, our research used coherence analysis in trust and mistrust situations to identify active brain regions (i.e., frontal, parietal, temporal, central, and occipital lobes) using topographic maps. Two electrodes were selected from each brain region, and a total of ten electrodes were recorded. This research included 30 participants (15 males and 15 females). In addition, any unusual neurological activities with typographic maps from the 30 participants were examined. From the total 20 trials, each participant's highest and lowest trust level trial was individually selected for data analysis. Hence, the selected trials were different for each participant.

Our research used topographic maps to identify simulated brain regions associated with trust and mistrust situations on automation. Therefore, it can help monitor the level of trust of human operators in complex automation by monitoring their neurological activities. In addition, it can be valuable when designing complicated automation, because considering human operators to trust automation for appropriate automation use is essential.

2. METHOD

2.1 Participants

30 participants (15 males and 15 females) participated in the experiment and were recruited at North Carolina A&T University. All participants were over 18 years old, had normal or corrected-to-normal vision, and did not suffer from neurological or psychiatric disorders. They were also able to read and comprehend the English language. The experiment did not discriminate against the participants based on race, age, gender, religion, or prior participation in other studies. No preference was given to left- or right-handed users, even though all participants could use a mouse and keyboard with their hands. Before the experiment, each participant read and signed a consent form.

Table 1. Demographic data of the participants

Participants	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
Age	18	19	19	20	19	21	20	22	19	19	20	20	20	21	22
Gender (Female/Male)	F	F	M	M	M	F	F	F	M	F	F	M	M	M	M
Participants	**P16**	**P17**	**P18**	**P19**	**P20**	**P21**	**P22**	**P23**	**P24**	**P25**	**P26**	**P27**	**P28**	**P29**	**P30**
Age	18	18	20	20	20	19	19	18	20	20	21	22	20	20	20
Gender (Female/Male)	F	W	F	F	M	F	F	F	M	F	F	M	M	M	M

2.2 Framework for Experimentation

This experiment used a simulated driving game to investigate how trust in automation affects decision-making and brain activities. Two distinct control modes were implemented: automatic (100% automation) and manual (0% automation), with no semi-automated option available (see Figure 1).

In the automatic control mode (100% automation), the system autonomously controls all vehicle operations. However, in the manual control mode (0% automation), the participant directly controls the vehicle using the keyboard and takes full responsibility for avoiding cars. Participants should select one of two control modes – automatic or manual – at the start of each trial. They could not switch modes during the trial. This setup placed participants in situations where they had to rely on their trust (or mistrust) in automation based on past performance to guide their decisions. For example, a participant might choose automation in earlier trials due to high performance but switch to manual control in later trials as mistrust in the automated system develops. The primary task is to avoid oncoming cars without getting into an accident, which serves as the performance measure. The performance was determined by preventing the number of cars from having any accidents. Any accident would end the driving simulation. If a participant avoided one car, it would be a 5% performance rate. If a participant avoided over 20 cars, it would be a 100% performance rate. After the experiment, participants completed a seven-point scale survey to assess their level of trust in automation quantitatively. This survey captured their subjective evaluation of the system's reliability and their confidence in its capabilities. According to the survey result, each participant's highest trust trial (trust) and lowest trust level trial (mistrust) from a total of 20 trials was individually selected for data analysis.

To induce trust in automation, the high-performance rate in automatic control was predetermined. This experiment examined only trust levels in automation, not in manual mode. To develop trust in automation, during training sessions, automatic control is designed to perform flawlessly, inducing trust in automation by avoiding all accidents. This ensures participants become familiar with its capacities and begin to trust the automated system. This perfect performance (100%) in the training sessions was designed to build confidence in the automation system's reliability, simulating a real-world scenario where automation consistently delivers high performance. In the first 10 trials, the automated system maintained high performance (100%), reinforcing participants' trust by avoiding oncoming cars. This consistent performance allowed participants to develop a sense of security and confidence in automation as a dependable mode of operation.

To induce mistrust in automation, the low-performance rate in automatic control was predetermined. To introduce mistrust in automation in later trials (11–20), the automated system's performance was significantly reduced, resulting in unexpected accidents. This sudden drop in reliability introduced uncertainty and challenged participants' trust in automation, simulating real-world scenarios where automated systems might fail unexpectedly or perform below expectations.

In the manual control mode, the participant controlled the vehicle to avoid cars entirely. During training sessions, participants practice manual control to become familiar with the driving simulation. During trials, the success of manual control depends entirely on the participant's skill. Unlike automatic control, the performance rate in manual control is not predetermined or manipulated; it reflects the participant's actual performance during the driving simulation. This difference allowed participants to compare their personal capabilities with the automated system's performance, potentially influencing their perception of the system's trustworthiness.

The experimental design effectively replicates real-world trust scenarios by requiring individuals to choose between automated systems and manual control. System reliability is manipulated to build trust through consistent performance, and later introduces mistrust due to failures. The combination of reliability manipulation, binary decision-making, and performance feedback provides a robust framework for examining trust dynamics, decision-making, and brain activity, capturing trust-building and mistrust-inducing situations.

Instruction
1. Choose any mode of control before it starts. You cannot change the mode during the game.
2. The game will end if you crash into another car.

Figure 1. Simulated driving of an automatic or manual control

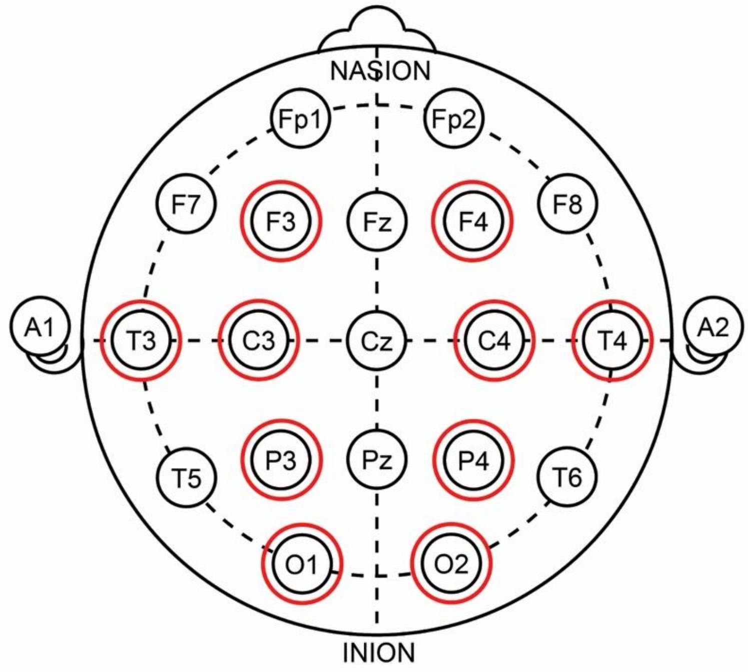


Figure 2. A modified 10–20 electrode placement system for the brain regions (Dong *et al*., 2015)

2.3 EEG Recording

The brainwaves were recorded using *g.HIamp* (256-multichannel amplifier), *g. GAMMAsys* (active electrode system with *g. GAMMAcap*), and *g. Recorder* (brain signal recording software) by a *g. tec* medical engineering company. This EEG recording followed the modified 10–20 electrode placement system. Only two electrodes in each region were selected to record five brain regions, including the frontal lobe (F3 and F4), temporal lobe (T3 and T4), central lobe (C3 and C4), parietal lobe (P3 and P4), and occipital lobe (O1 and O2) (Figure 2). Each participant wore an EEG cap (*g. GAMMAcap*) during the experiment. Then, only the selected ten cap electrodes were made of abrasive electrolyte gel using a syringe. The sampling frequency was 256 Hz, the high-frequency filter was 60 Hz, and the low-frequency filter was 0.1 Hz. Raw brainwaves included artifacts such as eye blinking, jaw clenching, and muscle movements. Before the experiment, the artifacts of each participant were recorded and marked. Before analyzing the EEG data, the artifacts were removed from the raw data using filters of the *g.Recorder* (brain signal recording software). This experiment was proved with IRB 17-0159.

2.4 Data Analysis

All participants' brainwaves were monitored and recorded throughout the 20 trials, including the decision-making of the control mode and the simulated driving moments. During the driving simulation moments, participants concentrated on watching the game in automatic control or playing the game with keyboards in manual control, so the driving moments were unrelated to their level of trust or mistrust. Therefore, only the brainwaves in decision-making at the start of each trial (automatic or manual control) were analyzed to find active brain regions related to trust and mistrust.

The EEG data from all 30 participants (15 males and 15 females) were analyzed. From the total 20 trials, each participant's highest and lowest trust level trial was individually selected for data analysis. First, each participant's normal brainwaves before stimuli were analyzed as a baseline. Then, each participant's brainwave with the highest level of trust was analyzed. Last, each participant's brainwave with the lowest level of trust (mistrust) was analyzed.

The brainwaves were classified with frequency ranges, such as alpha (α, 8–13 Hz), beta (β, 13–30 Hz), and gamma (γ, 30–60 Hz), by using power spectrum analysis (Ameera and Ibrahim, 2019). Following the power spectrum analysis, coherence analysis was conducted to investigate functional connectivity in the brain regions. The degree of phase stability or jitter between two signals in each frequency range was measured as coherence (Bowyer, 2016).

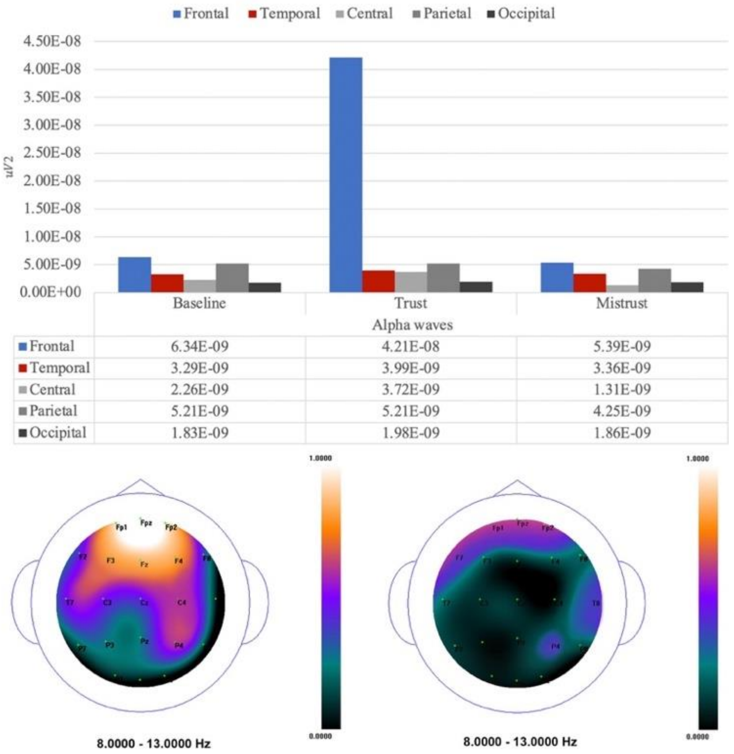
The study utilized representative electrode positions from the 10–20 systems, including electrodes for each part of the brain, namely the frontal lobe (F3 and F4), temporal lobe (T3 and T4), parietal lobe (P3 and P4), and occipital lobe (O1 and O2). A coherence value of 1 was achieved when the phase difference between two signals was constant; a coherence value of 0 was achieved when the phase difference between two signals was random. The square of cross-spectrum P_{ab} must be divided by the power spectrum $P_a(f)$and multiplied by the power spectrum $P_b(f)$ to achieve coherence when two channels (a and b) are recorded from a specific frequency range (f), as in (1).

$$Coh_{ab}(f) = \frac{P_{ab}(f)^2}{[P_a(f) \times P_b(f)]} \tag{1}$$

3. RESULTS

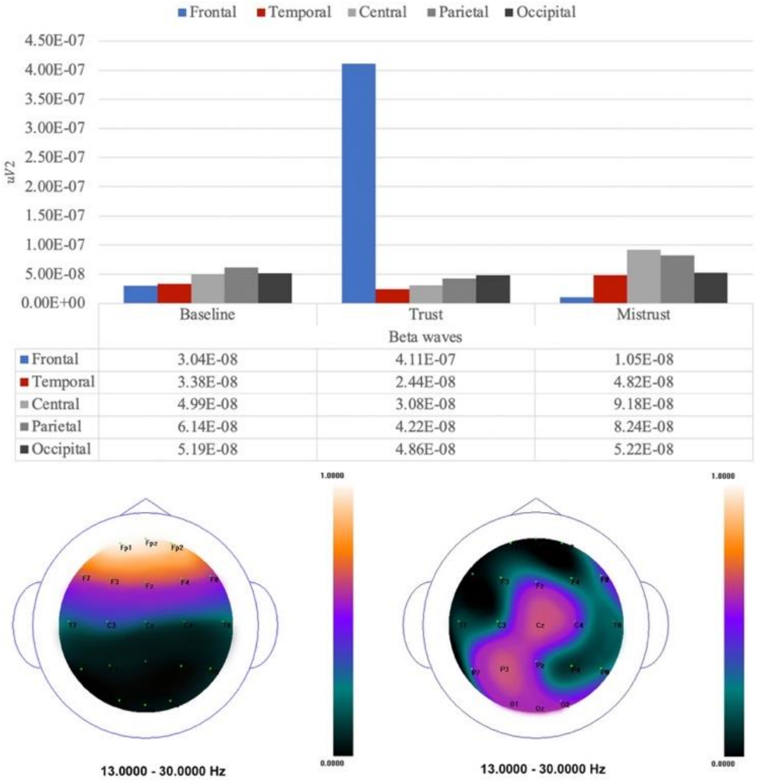
3.1 Comparison of Alpha, Beta, and Gamma Waves

Figure 3 shows a comparison of the alpha waves for the stimulated brain regions for the baseline, trust, and mistrust. The frontal lobe (4.21E-08 uV^2) of the alpha waves in the trust situation were highly stimulated compared to the other regions. According to the topographic maps, the alpha waves in the frontal lobe showed active connectivity for the trust situations; however, the frontal lobes (5.39E-09 uV^2) showed little connectivity for the mistrust situations. Figure 4 shows a comparison of the beta waves for the stimulated brain regions to the baseline, trust, and mistrust situations. The frontal lobe (4.11E-07 uV^2) of beta waves in the trust situation was highly stimulated compared to the other regions. According to the topographic maps, the beta waves in the frontal lobe showed active connectivity in the trust situations; however, the central and parietal lobes showed little connectivity in the mistrust situations. Figure 5 compares stimulated brain regions for the gamma waves to the baseline, trust, and mistrust situations. The temporal lobe (1.95E-08 uV^2) of gamma waves in the mistrust situation was highly stimulated compared to the other regions. According to the topographic maps, the gamma waves in the temporal lobe for the mistrust situation showed active connectivity, but the gamma waves in the right temporal, right central, and occipital lobes for the trust situation showed little connectivity.



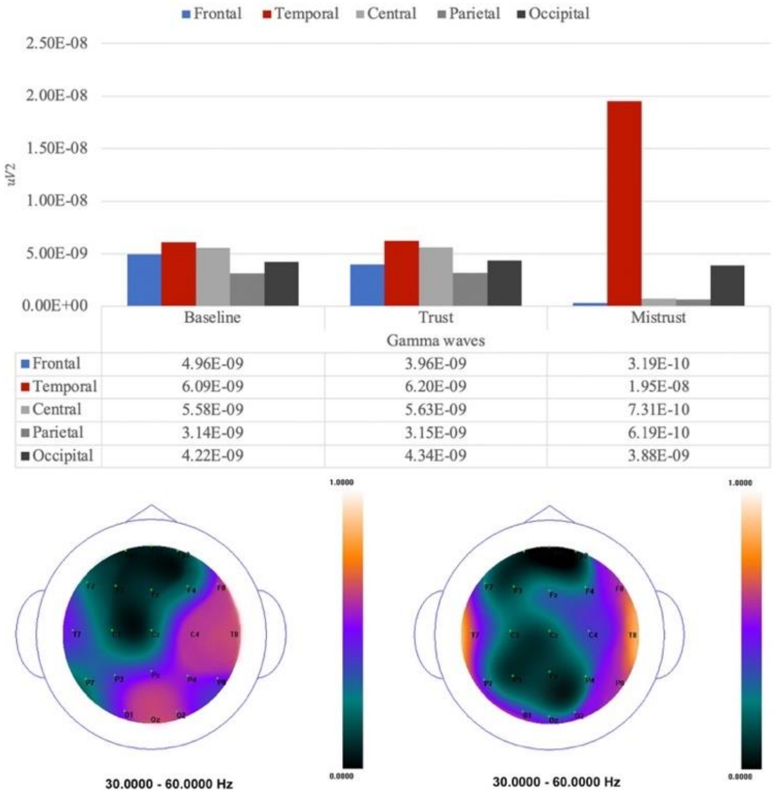
	Baseline	Trust	Mistrust
	Alpha waves		
■ Frontal	6.34E-09	4.21E-08	5.39E-09
■ Temporal	3.29E-09	3.99E-09	3.36E-09
■ Central	2.26E-09	3.72E-09	1.31E-09
■ Parietal	5.21E-09	5.21E-09	4.25E-09
■ Occipital	1.83E-09	1.98E-09	1.86E-09

Figure 3. Comparison of the brain regions in alpha waves and the topographic map in trust (left) and mistrust (right)



	Baseline	Trust	Mistrust
	Beta waves		
■ Frontal	3.04E-08	4.11E-07	1.05E-08
■ Temporal	3.38E-08	2.44E-08	4.82E-08
■ Central	4.99E-08	3.08E-08	9.18E-08
■ Parietal	6.14E-08	4.22E-08	8.24E-08
■ Occipital	5.19E-08	4.86E-08	5.22E-08

Figure 4. Comparison of the brain regions in beta waves and the topographic map in trust (left) and mistrust (right)



	Baseline	Trust	Mistrust
■ Frontal	4.96E-09	3.96E-09	3.19E-10
■ Temporal	6.09E-09	6.20E-09	1.95E-08
■ Central	5.58E-09	5.63E-09	7.31E-10
■ Parietal	3.14E-09	3.15E-09	6.19E-10
■ Occipital	4.22E-09	4.34E-09	3.88E-09

Figure 5. Comparison of the brain regions in gamma waves and the topographic map in trust (left) and mistrust (right)

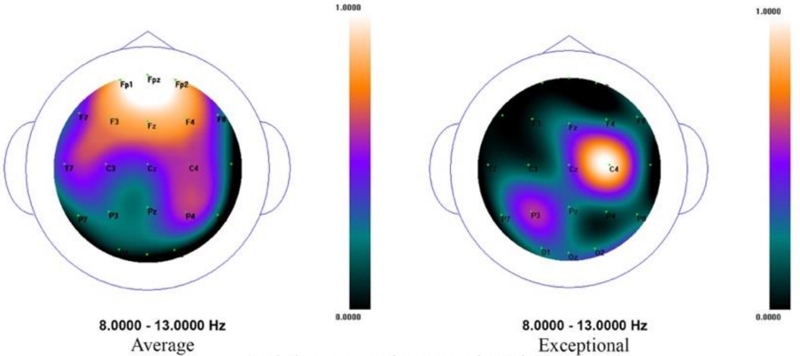
3.2 Comparison of Average and Exceptional Topographic Maps

By comparing average and exceptional topographic maps of the alpha waves in the trust situation, the average topographic map exhibited active connectivity in the frontal lobe, while the exceptional topographic map depicted active connectivity in the central lobes (a in Figure 6). It was from participant #16, who showed decreased alpha waves. In contrast, 29 of 30 participants possessed increased alpha waves. This could indicate unusual neural activity from individual differences. This might suggest that participant #16 was less relaxed, possibly due to heightened attention, stress, or discomfort in the trust situation.

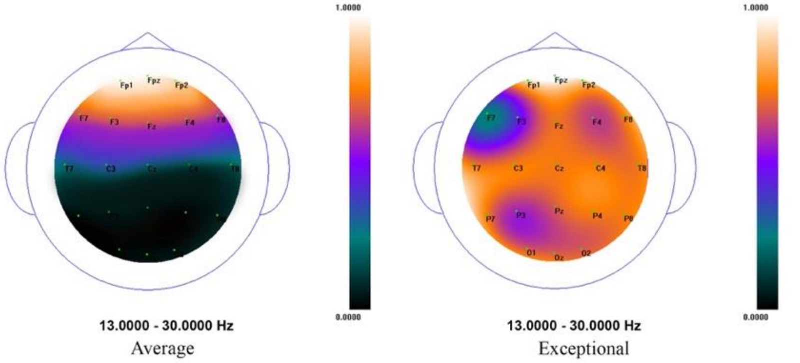
When comparing average and exceptional topographic maps of the beta waves in the trust situation, the average map demonstrated active connectivity in the frontal lobe. However, the exceptional map showed active connectivity in all lobes (b in Figure 6). It was from participant #16, who showed a significant increase in beta waves from the baseline. This could show unusual neural activity due to individual differences. It also suggests that participant #16 had increased alertness, heightened focus, or more significant cognitive effort in the trust situation.

By comparing average and exceptional topographic maps of the gamma waves in the mistrust situation, the average topographic map had active connectivity in the temporal lobes. However, the exceptional topographic map illustrated active connectivity in the occipital lobe (c in Figure 6). This exceptional topographic map was from participant #23, who had increased gamma waves in the occipital lobe when 29 of 30 participants had increased gamma waves in the temporal lobes. This could show unusual neural activity due to individual differences. The exceptional topographic map suggests that participant #23 may have focused more on visual elements related to the occipital lobe during the mistrust situation, unlike the others, who focused on cognitive or emotional processing associated with the temporal lobe.

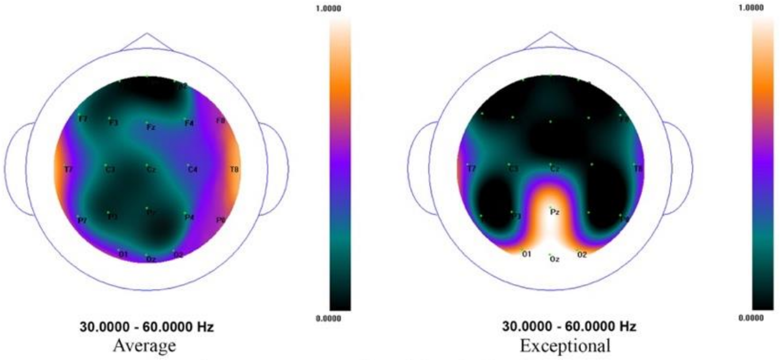
The outliers (participants #16 and #23) could impact the findings and future research. Understanding these variations is essential for refining trust and mistrust models of brain activity. While the findings of this research using averaged data suggested general neurological activities (i.e., the frontal lobe in alpha and beta waves for trust and the temporal lobe in gamma waves for mistrust), the neurological response may not be entirely consistent across populations, requiring caution when generalizing the results. Participant #16 (female, 18 years old) shows decreasing alpha and increasing beta waves related to heightened attention and alertness in the trust situation. Participant #23 (female, 18 years old) shows increasing gamma waves in the occipital lobe related to visual stimuli in the mistrust situation. To investigate the outliers further, the research needs to examine demographic factors such as gender and age, and physiological factors such as stress levels and personal traits to explain the participants' unique brain activities. In addition, it needs to acknowledge individual differences in neural responses to trust and mistrust situations.



a) alpha waves in trust situation



b) beta waves in trust situation



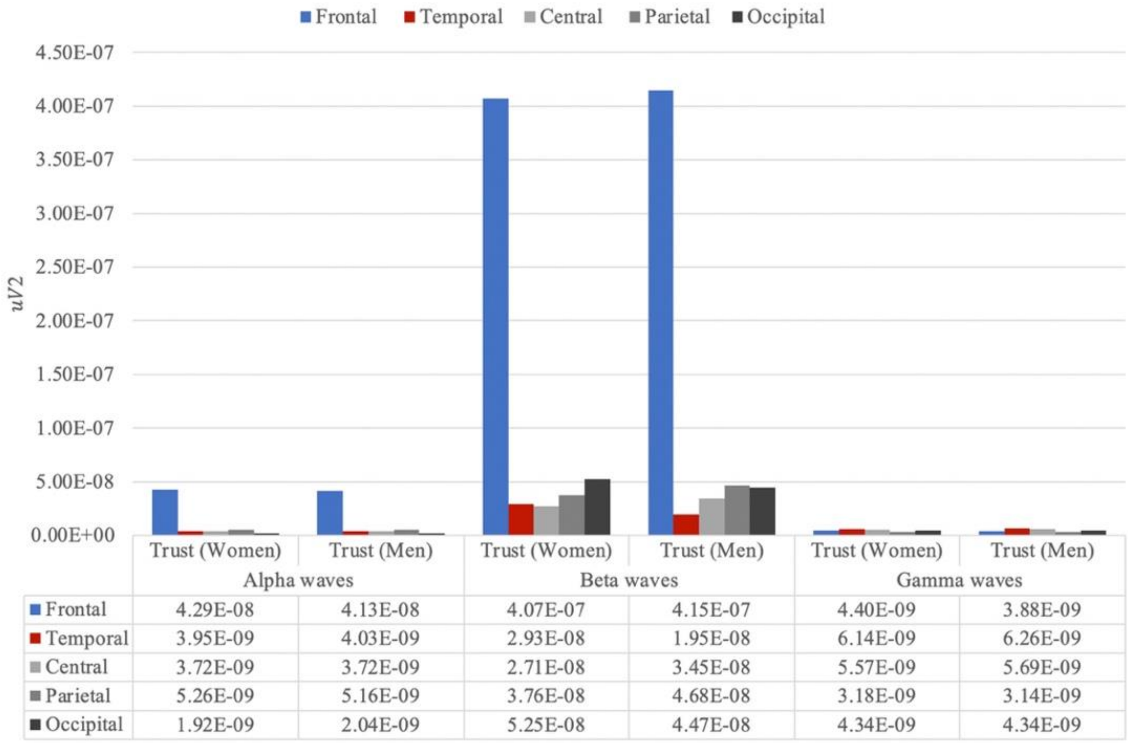
c) gamma waves in mistrust situation

Figure 6. Average and exceptional topographic maps of the alpha, beta, and gamma waves

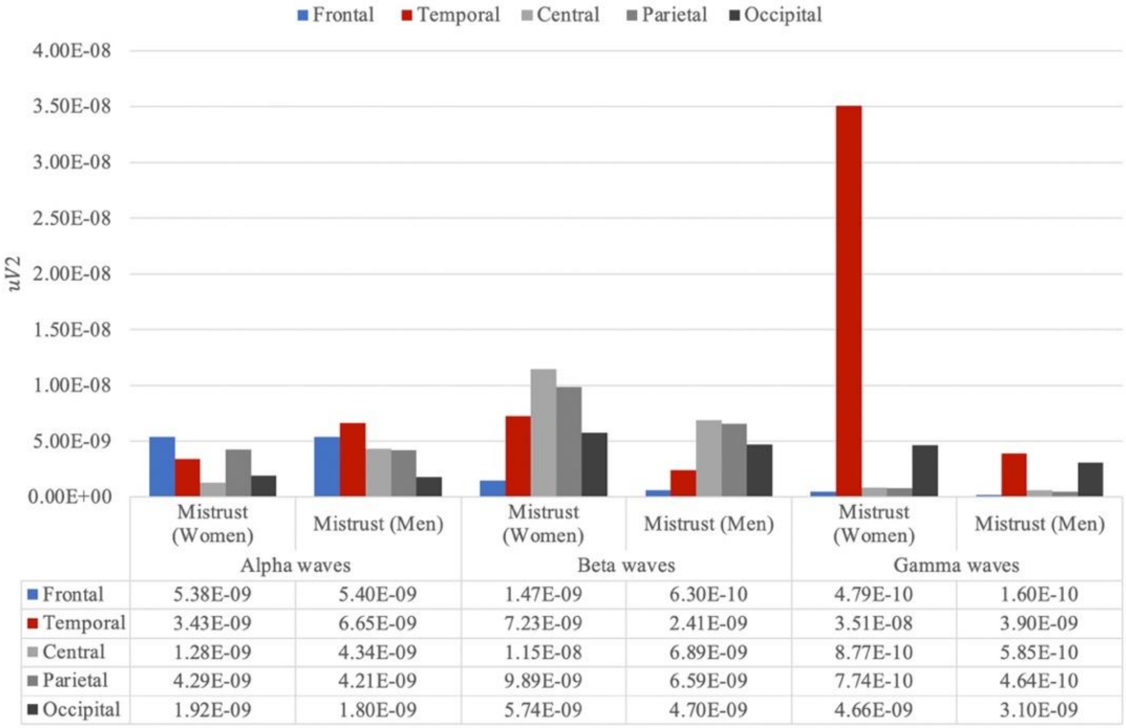
3.3 Comparison of Gender Differences in Trust and Mistrust

In the trust situation, the women's and men's brainwaves were compared in the stimulated brain regions in the alpha, beta, and gamma waves (see Figure 7). In alpha waves, the frontal lobes are activated in both women (4.29E-08 uV^2) and men (4.13E-08uV^2). In beta waves, the frontal lobes are strongly activated in both women (4.07E-07 uV^2) and men (4.15E-10uV^2). In the trust situation, the frontal lobes in alpha and gamma waves were stimulated by both women and men. No distinct gender difference existed in the situation of trust.

However, the mistrust situation differed. In the mistrust situation, the women's and men's brainwaves were compared in the stimulated brain regions in the alpha, beta, and gamma waves (see Figure 7). The gamma waves in the women's temporal area (3.51E-10uV^2) were much stronger than the men's (3.90E-09uV^2) in the mistrust situations. Moreover, the mistrust stimulated other brain regions in women, including the frontal, central, parietal, and occipital regions, with beta waves.



	Alpha waves		Beta waves		Gamma waves	
	Trust (Women)	Trust (Men)	Trust (Women)	Trust (Men)	Trust (Women)	Trust (Men)
■ Frontal	4.29E-08	4.13E-08	4.07E-07	4.15E-07	4.40E-09	3.88E-09
■ Temporal	3.95E-09	4.03E-09	2.93E-08	1.95E-08	6.14E-09	6.26E-09
■ Central	3.72E-09	3.72E-09	2.71E-08	3.45E-08	5.57E-09	5.69E-09
■ Parietal	5.26E-09	5.16E-09	3.76E-08	4.68E-08	3.18E-09	3.14E-09
■ Occipital	1.92E-09	2.04E-09	5.25E-08	4.47E-08	4.34E-09	4.34E-09



	Alpha waves		Beta waves		Gamma waves	
	Mistrust (Women)	Mistrust (Men)	Mistrust (Women)	Mistrust (Men)	Mistrust (Women)	Mistrust (Men)
■ Frontal	5.38E-09	5.40E-09	1.47E-09	6.30E-10	4.79E-10	1.60E-10
■ Temporal	3.43E-09	6.65E-09	7.23E-09	2.41E-09	3.51E-08	3.90E-09
■ Central	1.28E-09	4.34E-09	1.15E-08	6.89E-09	8.77E-10	5.85E-10
■ Parietal	4.29E-09	4.21E-09	9.89E-09	6.59E-09	7.74E-10	4.64E-10
■ Occipital	1.92E-09	1.80E-09	5.74E-09	4.70E-09	4.66E-09	3.10E-09

Figure 7. Comparison of stimulated brain regions in trust in the alpha, beta, and gamma waves by genders in trust (top) and mistrust (bottom)

4. DISCUSSION

The first section examines previous studies on neurological activities in brain waves related to the results of this study. Brain waves are composed of varying frequencies, enabling their analysis based on specific frequency ranges. Power spectrum analysis is used to analyze brain waves into distinct frequency bands: 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). The brain waves are related to various states of consciousness and mental activities. A comparison of brainwaves shows that alpha and beta waves are more prominent in the trust situation, while gamma waves are more prominent in the mistrust situation.

Alpha waves are present when individuals are awake but relaxed, with minimal information processing and attention. They are associated with a relaxed and calm mental state, so there is strong alpha wave activity during meditation (Cahn and Polich, 2006). Alpha waves are associated with memory recall, pain relief, and the reduction of stress and anxiety (Aguiar *et al*., 2022). They are also related to trust situations, which can be relaxed without stress and tension.

Beta waves involve tasks requiring concentration, problem-solving, judgment, and decision-making. Beta waves serve as a valuable measure of cognitive activity (Lundqvist *et al*., 2024). High beta waves are associated with stress or anxiety due to heightened mental activities (Leaf *et al*., 2023). A lack of sufficient beta activity can lead to mental and emotional disorders, including depression, attention deficit disorder (ADD), and insomnia (Egner and Gruzelier, 2004). Beta waves enhance concentration, attention, and emotional regulation (Siever, 2004). Beta waves are related to trust situations, which could increase attention and help problem-solving and decision-making.

Gamma waves are the fastest brain waves related to anxiety and advanced cognitive functions like reasoning and judgment. They are critical in idea generation, language use, memory processing, and learning (Vieira *et al*., 2024). Gamma waves are particularly active when individuals utilize short-term memory to recognize objects, sounds, or tactile sensations (Lupu *et al*., 2020). Gamma waves are also related to mistrust situations, which can interrupt mental activity with increased stress and anxiety.

The second section examines existing literature investigating neurological activities in brain regions relevant to understanding this research's findings (i.e., the frontal lobe for trust and the temporal lobe for mistrust). First, understanding the frontal lobe's function is crucial. The frontal lobe is an essential region of the brain often referred to as the "control tower" due to its association with memory, willpower, logical thinking, adjustment of activities in the other brain regions, and control of emotions and impulses (Drnec *et al*., 2016). Moreover, the frontal lobe is associated with problem-solving, judgment, attention, organization, planning, and anticipation (Fuster, 2013). Notably, the prefrontal cortex (PFC), the cerebral cortex covering the front part of the frontal lobe, performs executive functions. These functions involve organizing and executing a series of actions for complex cognitive goals by predicting the consequences of current activities and making decisions by differentiating between conflicting thoughts and determining good and bad (Yang and Raine, 2009). The prefrontal cortex needs direct access to sensory, motor, and mnemonic information to conduct actions on time (Fuster, 2013). A damaged prefrontal cortex could result in antisocial, violent, and psychopathic behaviors (Yang and Raine, 2009).

How does trust relate to the frontal lobe? Trust can be a "decision aid" when human operators decide to use automation, making understanding the decision-making process critical. A study showed the relationship between the prefrontal area and risk-taking behavior during decision-making. Gianotti *et al*. (2009) found that the decision-making process regarding risk can stimulate neurological activities in the right prefrontal cortex concerning an individual's risk-taking behavior. Risk-taking behavior can also be associated with human operators' strategies when using automation, because an individual with a greater risk-taking behavior will tend to overtrust and overuse automation even when the operator recognizes an error or fault with automation. Cohen and Donner (2013) used EEG to investigate conflict processing in decision-making and examine neural oscillations in the medial prefrontal regions regarding monitoring conflict and activities involving a goal. They found that theta-band oscillations in the medial frontal cortex are time-locked, not phase-locked, to stimuli responding to conflict in a specific condition. In other words, theta-band oscillations in the medial frontal cortex can be a neurological indicator for detecting conflict processing during decision-making. Krueger *et al*. (2007) suggest that conditional trust assumes one's partner is self-interested. Therefore, trust can easily affect collective decisions each time; thus, it is hard to maintain. Conditional trust increases the activity of the ventral tegmental region (frontal lobe), associated with the reward system, by expecting and receiving a consequence without surprise (Takahashi *et al*., 2009). Dimoka (2011) suggests that psychological processes related to trust involve expecting rewards, engaging in cooperative behavior, and accepting uncertainty. Several MRI studies have revealed that the lateral orbitofrontal cortex and the medial orbital frontal cortex relate to the risk and reward process (Rangel and Hare, 2010).

The temporal lobe is essential in executing complex functions and is interconnected with other cortical regions (Barense *et al*., 2010). Specifically, it is associated with the perception of visual and auditory sensations related to speech and language processing (Meyer *et al*., 2005), language comprehension, long-term memory storage, facial and object recognition (Yue and Martin, 2022), and emotion. Deep within the temporal lobe, the amygdala can control major affective activities such as friendship, love, and affection, and expresses moods like fear, rage, and aggression (Aboytes *et al*., 2022). The amygdala is the center for identifying danger, helping self-protection when activated, and bringing fear and anxiety (Fox and Shackman, 2019).

How does the temporal lobe relate to mistrust? Winston *et al*. (2013) depicted that trust is correlated to the frontopolar cortex (frontal lobe) and distrust is correlated to the right amygdala and the right insula (temporal lobe) by investigating neural correlations of human trust based on facial appearance. The results revealed that untrustworthy faces evoked intense activity in the amygdala, right insula (temporal lobe), and right superior temporal sulcus (STS). The amygdala region is highly associated with human emotions such as danger and threat (Jaramillo *et al*., 2021). Dimoka (2011) suggested that trust is associated with several brain regions, including the caudate nucleus, putamen, anterior paracingulate cortex, and orbitofrontal cortex (frontal lobes). Conversely, distrust is related to the amygdala and insular cortex (temporal lobes). The amygdala plays a vital role in the defense response to fear (Sun *et al*., 2020), while the insular cortex is activated in response to feelings of disgust (Schienle *et al*., 2020). Psychological activities associated with distrust are based on processes involving negative emotions, such as fear and disgust.

Reviewing the neurological activities of brain regions in previous studies can help us better understand the role of decision-making. Trust situations can stimulate the frontal lobe because they relate to cognitive function, including predicting the future, anticipating rewards, and measuring uncertainty. Mistrust can stimulate the temporal lobe because it relates to intense negative emotions, such as fear of loss, caution, anger, hate, and betrayal. When mistrust is present, the temporal lobe can be stimulated because it is associated with negative emotions such as fear and disgust from danger and threat. Future studies should investigate neural correlations between trust and brain activity during human-machine decision-making processes. These studies should consider various factors such as risk, reward, conflict, danger, and threat.

Automation becomes complex for sophisticated tasks. This research can contribute to monitoring the psychological state of the human operator for the proper use of automation in uncertain or urgent situations (e.g., automated driving, air traffic control, and healthcare robots). For example, suppose an operator's brain activity indicates high stress or mistrust (such as increased gamma waves associated with anxiety or cognitive load). In that case, the system can adjust its behavior by switching to automatic control or providing additional feedback to reassure the operator to reduce stress. In real-time, this system could detect when an operator's trust in the automation is decreasing (e.g., via changes in alpha or beta waves) and trigger alerts or suggestions to help the operator regain confidence, preventing errors due to mistrust.

In addition, this research can contribute to developing personalized training programs in automation design by checking the human operators' level of trust. This research can be used to train human operators not only on how to use automation but also on how to build and maintain trust in automated systems. By monitoring neural activities during training, automation designers can determine when an operator can use the automated systems with adequate trust (e.g., stable alpha and beta waves). It can help to rebuild trust after automation fails (e.g., an autonomous vehicle's malfunction). Neuroimaging technology can assess the operator's level of stress and mistrust after such a failure. Automation systems can implement training programs to rebuild trust, such as offering detailed explanations of what went wrong, showing the system's actions to prevent future problems, and suggesting manual control options.

5. CONCLUSION

This research investigated the brain waves and brain regions stimulated by trust and mistrust in the use of automation. By comparing the brainwaves, the alpha and beta waves are stronger in the trust situation, while the gamma waves are stronger in the mistrust situation (see Figure 3-5). By comparing the brain regions, the frontal lobe showed active connectivity for both alpha and beta waves in the trust situation. In contrast, the temporal lobe showed active connectivity for the gamma waves in the mistrust situation (see Figure 3-5).

Based on the exceptional topographic maps (see Figure 6), participant #16 showed a decline in alpha waves and an increase in beta waves, indicating enhanced attention and alertness during the trust situation. In contrast, participant #23 displayed increased gamma waves in the occipital lobe, which were linked to visual stimuli in the mistrust situation. To explore the outliers more deeply, future research should involve more participants and analyze demographic and physiological elements to clarify the distinct brain activities of the participants. Additionally, it should recognize the individual variations in neural responses to both trust and mistrust situations.

Additionally, this research compared how women and men differ in trust and mistrust situations. According to gender differences, trust situations are similar both in women and men, but mistrust situations differ. By comparing brainwaves in women and men, both women and men have strong alpha and beta waves in trust situations. However, women showed stronger gamma waves than men in mistrust situations. It means that women could have more stress and anxiety in a mistrust situation. By comparing brain regions in women and men, no significant differences were found between genders in the trust situation. However, the mistrust stimulated women's temporal regions strongly in the gamma waves and all regions slightly in the beta waves. Other studies also align with the findings of this study regarding gender differences. Riedl *et al*. (2010) found that, using fMRI, women's brain areas were more activated than men's in online trust. Another study demonstrated that women are more sensitive to risk-taking than men (Charness and Gneezy, 2012). According to the study of trust and gendered perspective, while trust appears to be similar across genders, distrust, and mistrust seem to differ across genders (Bunting *et al.*, 2021).

To enhance trust in an automated workplace, adjustments in brainwaves could improve safety and performance. Creating a workplace that supports transparency, reliability, and predictability in automation can encourage alpha and beta waves related to trust while reducing gamma waves related to mistrust. In the trust situation, both male and female workers are encouraged to amplify alpha and beta waves because alpha waves are associated with a calm mental state, and beta waves are related to attention and decision-making (Cahn and Polich, 2006; Rassi *et al.*, 2023). In the mistrust situations, females exhibited stronger gamma waves than males. Male workers need to increase gamma waves to heighten their awareness of errors or failures of automation. Female workers need to alleviate stress and promote trust by offering reassurance about the safety and reliability of the automation system.

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