Detecting Deceptive Responses Due to Psychological Bias by the Probability Density Function of EEG Content Rate Dynamics During NEO-FFI Answering

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Abstract— **The NEO Five-Factor Inventory (NEO-FFI) is a psychological scale used to assess personality based on five major traits. Although widely adopted, its reliability can be compromised due to susceptibility to psychological biases during self-reporting.**

This study proposes a method for detecting biased responses by analyzing EEG signals recorded while participants answer NEO-FFI questions. As features, we extracted parameters derived from probability density functions fitted to the temporal variations of content rates in five EEG bands—alpha, beta, theta, delta, and gamma—measured across eight brain regions (frontal, temporal, parietal, and occipital lobes). Frequency distributions were first developed from these temporal signals, and the resulting fitted parameters served as input features.

A support vector machine (SVM) was trained using these features to detect each response as either biased or unbiased. In an experimental study involving 23 participants aged 19 to 23, the proposed method achieved an average accuracy of 0.64, precision of 0.75, specificity of 0.41, recall of 0.74, negative predictive value of 0.42, and an F1 score of 0.71. These results indicate that the proposed approach effectively identifies biased responses and improves the reliability of personality assessment using the NEO-FFI.

I. Introduction

The NEO Five-Factor Inventory (NEO-FFI) is a widely used psychological scale for quantitatively assessing human personality in psychology [1–5]. Based on Goldberg's Big Five theory, which characterizes personality through five factors: neuroticism (N), extraversion (E), openness (O), agreeableness (A), and conscientiousness (C), the NEO-FFI was developed by Costa et al. [6][7]. The inventory consisted of 60 questions, with 12 questions assigned to each personality factor. Respondents answered each question using a five-point Likert scale (0–4), and the total scores were used to assess each trait.

However, responses to the NEO-FFI can be compromised by psychological biases, such as social desirability, prompting individuals to answer in ways that portrays themselves more favorably [8][9]. If biased responses are included in the assessment, the reliability of the results may be compromised. Therefore, identifying whether each response is influenced by psychological bias can enhance the reliability of personality assessments.

NEO-FFI questions are processed as emotional stimuli in the brain [10–12], and these stimuli are considered pleasant or unpleasant in the amygdala [13–18]. This judgment can induce a psychological bias [19–22], which subsequently activates the autonomic nervous and endocrine systems, resulting in behavioral and cognitive changes [23–26]. Furthermore, when a psychological bias is induced, cognitive dissonance arises between the true self and socially desirable self, increasing the cognitive load on the brain [27–30]. These findings suggest a relationship between the NEO-FFI questions and neural activity.

Based on this, our previous studies explored several methods for detecting deceptive responses using EEG recorded during NEO-FFI. These include detection based on occipital beta waves [31], detection using features extracted from brain activity networks [32], detection based on factor analysis of EEG signals, and the use of factor loadings related to psychological bias [33].

In this study, we propose a method to detect deceptive responses by analyzing the time-varying dynamics of the α, β, θ, δ, and γ EEG bands in the time–frequency domain which has not yet been explored during NEO-FFI answering. These dynamics were modeled using probability density functions for each EEG band to detect bias-induced responses.

II. Proposed Method

A. Probability Density Functions Based on Temporal Variations in EEG Band Content Rates Induced by Psychological Bias During NEO-FFI Responses

When psychological bias is induced during responses to the NEO-FFI questions, the content rate $C_{n,q,b}(t)$ at time t for each of the five EEG bands $BW=\{\alpha$–wave:8–13 Hz, β–wave:14–30 Hz, θ–wave:4–7 Hz, δ–wave:0.5–3 Hz, γ–wave:30–70 Hz$\}$ fluctuates over time. Here, $n \in p$ denotes one of the EEG electrode positions based on the international 10–20 system, with $p=\{$Fpz, Fz, Pz, Cz, T3, T4, O1, O2$\}$. The variable q indicates the question number within the NEO-FFI, and $b \in BW$ denotes the EEG frequency band. In the proposed method, the probability density function of $C_{n,q,b}(t)$ is denoted as $P(C_{n,q,b};v_{n,q,b})$, where $v_{n,q,b}$ represents the parameters characterizing the distribution. As illustrated in Fig. 1, we assume that the cognitive load associated with psychological bias affects parameters $v_{n,q,b}$ of the distribution $P(C_{n,q,b};v_{n,q,b})$.

This probability density function, $P(C_{n,q,b};v_{n,q,b})$, is developed separately for each EEG band, brain region, and question in NEO-FFI.

B. Signal Processing for Detecting the Presence of Psychological Bias from NEO-FFI Responses

This section describes the signal processing procedure used to derive the probability density function $P(C_{n,q,b};v_{n,q,b})$ for each EEG signal measured by an EEG device and detect the presence or absence of psychological bias.

An overview of the proposed signal processing method is shown in Fig. 2.

In the proposed method, EEG signals are recorded from the brain region n while a participant responds to a given NEO-FFI question q. A notch filter is applied to the recorded EEG signal to remove power line interference (hum noise), resulting in the filtered signal $x_n(k)$.

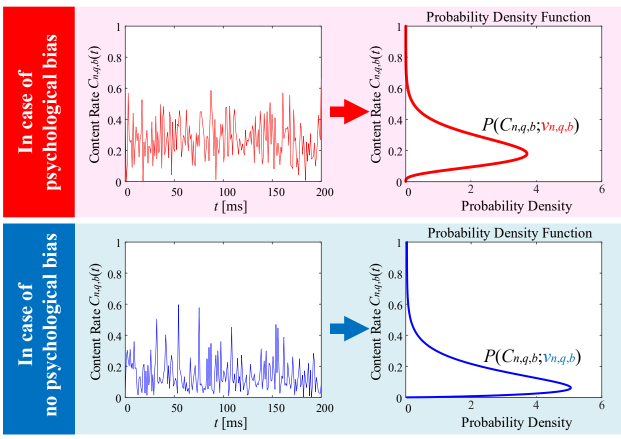

Fig.1 Effect of psychological bias on the parameter $v_{n,q,b}$ of the probability density function $P(C_{n,q,b};v_{n,q,b})$.

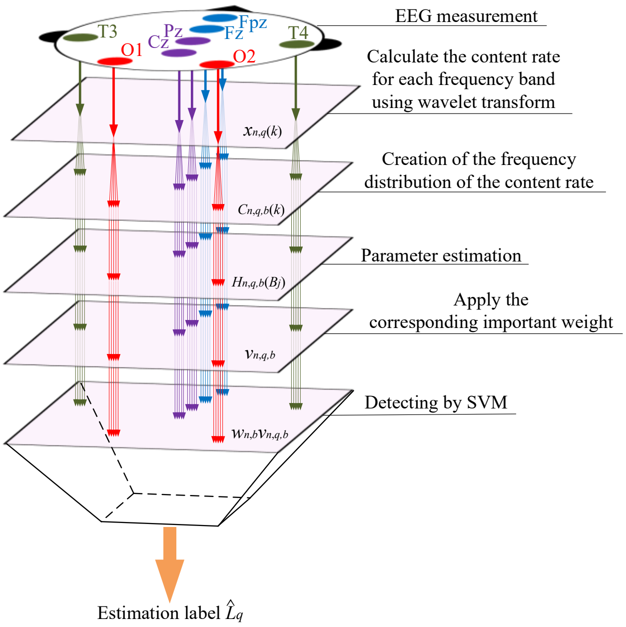

Fig.2 Signal processing flow for detecting answers affected by psychological bias.

Here, $k(=1, 2, \ldots, N_d)$ represents discrete time steps sampled at intervals of Δt, and N_d denotes the number of data points for question q.

Based on the EEG signals $x_{n,q}(k)$ measured in each brain region, a frequency distribution of the content rates was developed by analyzing the temporal variation of the five types of EEG. A wavelet transform was applied to $x_{n,q}(k)$ to compute the spectral intensity $S_{n,q}(k,f)$ at time k and frequency f: In the proposed method, for any EEG $b \in BW$, the frequency band is defined as $f_{b,low}$–$f_{b,high}$. The content rate $C_{n,q,b}(k)(=0–1)$ of EEG b at time step k while responding to question q is calculated using Equation (1). Here, the frequency $f(=0, 2\Delta f, 3\Delta f, \ldots, f_N)$, where Δf denotes the frequency resolution and f_N denotes the Nyquist frequency. As the discrete frequency set does not always include the exact values of $f_{b,low}$ and $f_{b,high}$, we define $\hat{f}_{b,low}$ and $\hat{f}_{b,high}$ as the discrete frequencies closest to $f_{b,low}$ and $f_{b,high}$, respectively, and use them to compute $C_{n,q,b}(k)$.

$$C_{n,q,b}(k) = \sum_{f=\hat{f}_{b,low}}^{\hat{f}_{b,high}} S_{n,q}(k,f) \Big/ \sum_{f=0}^{f_N} S_{n,q}(k,f) \qquad (1)$$

Subsequently, the content rate $C_{n,q,b}(k)$ of EEG b is treated as a random variable, and the interval [0,1] is divided into d equal-width bins $B_j (j=1, 2, \ldots, d)$. The frequency $H_{n,q,b}(B_j)$, representing the number of occurrences of $C_{n,q,b}(k)$ falling into each bin B_j, was calculated using the indicator function r, as shown in Equation (2).

$$H_{n,q,b}(B_j) = \sum_{k=0}^{N_d} r(C_{n,q,b}(k) \in B_j) \qquad (2)$$

where, $r(C_{n,q,b}(k) \in B_j) = \begin{cases} 1 & if\ C_{n,q,b}(k) \in B_j \\ 0 & otherwise \end{cases}$

Next, to estimate parameters $v_{n,q,b}$, the frequencies $H_{n,q,b}(B_j)$ are fitted to the probability density function $P(C_{n,q,b};v_{n,q,b})$. The resulting parameters $v_{n,q,b}$ are then aggregated based on whether the corresponding responses were affected by a psychological bias. In the proposed method, the product of the calculated parameters $v_{n,q,b}$ and their corresponding importance weight $w_{n,b}$(=0–1), denoted by $w_{n,b}v_{n,q,b}$, was used as a feature representing the probability density function based on the temporal fluctuations of the EEG content rate.

Using the features $w_{n,b}v_{n,q,b}$ obtained for all questions, brain regions, and EEG, a binary detecting was performed using a support vector machine (SVM) to detect whether the response to question q was affected by psychological bias. In the training phase of the SVM, N_S participants responded to NEO-FFI. For each question, a label $L_q \in \{0,1\}$ is assigned: 0 if the response is unaffected by psychological bias (i.e., answered honestly), and 1 if the response is affected by psychological bias (i.e., answered deceptively). Labels L_q were used as references, and features $w_{n,b}v_{n,q,b}$ were used to train the detecting model. In the detecting phase, for a new participant whose label L_q is unknown, the features $w_{n,b}v_{n,q,b}$ are extracted from the EEG data recorded while answering question q. These features were then input into the trained model to predict the label $\hat{L}_q$ for that question.

III. Verification Experiment

A. Experiment Procedures

To validate the effectiveness of the proposed method, an experimental study was conducted.

The participants were 23 individuals aged between 19 and 23 years. Each participant was presented with a randomized version of the 12-question NEO-FFI questionnaire of neuroticism on a PC display. They were instructed to respond to each question on a five-point Likert scale (0–4) using a wireless keyboard. During this session, the participants were instructed to respond deceptively— that is, to intentionally select answers that differed from their true feelings— to the questions they wished to answer in a socially desirable way. The responses collected in this session are referred to as (A1).

To evaluate the proposed method, it is necessary to assign a label L_q to each question q in (A1) to indicate whether the response is genuine or deceptive. Therefore, in the validation experiment, the participants were asked to complete another randomized version of the NEO-FFI questionnaire in the same 0–4 point format. However, the participants were instructed to answer each question honestly. The responses from the second session are referred to as (A0).

In this study, for each question q, if the response value in (A1) matched the corresponding response in (A0), the question was labeled honest and assigned L_q=0, indicating no psychological bias. If there was a discrepancy between the (A1) and (A0) responses, the question was considered deceptive, influenced by psychological bias, and labeled L_q=1. The order of completion of (A0) and (A1) was randomized for each participant to control for ordering effects.

During the (A1) session, the participants' EEG signals were recorded at each electrode region p using a portable multipurpose biopotential amplifier (Polymate AP1542; Miyuki Giken Co., Ltd.). Based on the proposed method, feature values were extracted from the EEG data for analysis.

This study was conducted with the approval of the Aoyama Gakuin University Ethics Committee (approval Number: H23–025).

B. Evaluation Method and Parameter Tuning

The detecting performance of the proposed method using an SVM was evaluated by leave-one-subject-out cross-validation. In this validation, data from 22 of 23 participants (i.e., N_S=22) were used for training the SVM, and the remaining participants' data were used for testing. To prevent class imbalance during the training phase, under-sampling was performed ten times to equalize the number of data samples with labels L_q=0 and L_q=1. This process yielded 230 confusion matrices (23 participants × 10 repetitions), as listed in Table 1.

For each confusion matrix, the following metrics were calculated using Equations (3)–(8): Accuracy, Positive Predictive Value (PPV), Negative Predictive Value (NPV), recall, specificity, and F1-score. The average value of 230 results was used to evaluate the validity of the proposed method. Furthermore, in this validation experiment, the importance weights $w_{n,b}$ for the features, kernel function of the SVM, cost parameter for penalizing detecting errors, gamma parameter for controlling the complexity of the decision boundary, and order parameter for the polynomial kernel were treated as genes in the Genetic Algorithm (GA) optimization process. The evaluation function of the GA was defined as the F1-score, and the algorithm evolved genes to maximize this score. The GA was run for 2000 generations with a population size of 50. Table 2 summarizes the probability distributions and the parameters $v_{n,q,b}$ used in the probability density function fitting process. The MATLAB function fitdist was used to fit the

Table 1 Confusion matrix.

		Measured Value	
		Negative	Positive
Predicted Value	Negative	TN	FN
	Positive	FP	TP

$$\text{Accuracy} = (TP + TN) \,/\, (TP + FP + FN + TN) \quad (3)$$

$$\text{PPV} = TP \,/\, (TP + FP) \quad (4)$$

$$\text{NPV} = TN \,/\, (TN + FN) \quad (5)$$

$$\text{Recall} = TP \,/\, (TP + FN) \quad (6)$$

$$\text{Specificity} = TN \,/\, (TN + FP) \quad (7)$$

$$\text{F1} - \text{score} = 2 \times (\text{PPV}) \times (\text{Recall}) \,/\, (\text{PPV} + \text{Recall}) \quad (8)$$

Table 2 The distribution and its parameters $v_{n,q,b}$ used for fitting the probability density function.

Number	Distribution name	$v_{n,q,b}$
1	Lognormal	μ : log-mean σ : log-standard deviation
2	Exponential	λ : rate
3	Weibull	k : shape λ: scale
4	Gamma	α : shape β : scale
5	Beta	α : left shape β : right shape
6	Extreme Value	μ : location σ : scale
7	Loglogistic	α : shape β : scale

distributions and estimate the parameters $v_{n,q,b}$, and the results were used to compare the effectiveness of each distribution in the proposed method.

IV. Result

Table 3 presents the results of the validation experiments. As shown in Table 3, the detecting using parameters $v_{n,q,b}$ of the gamma distribution as features achieved the highest F1 score among all distributions. In this case, a high positive predictive value (PPV) and recall indicate strong performance in detecting positive (biased) responses. Conversely, the low negative predictive value (NPV) and specificity suggest difficulty in correctly identifying negative (unbiased) responses. The contribution of each feature $w_{n,b}$ to the detecting using gamma distribution is shown in Fig. 3. Because the gamma distribution has two parameters, the figure shows the sum of the two corresponding feature weights. These results indicate that the parameters of the alpha wave at region T4 had the greatest influence on the detecting performance.

Furthermore, Fig. 4 shows the probability density functions of the alpha wave at region T4 for the participant with the highest detecting accuracy, comparing questions affected by psychological bias to those unaffected. The vertical axis is on a logarithmic scale to make the graph shape easier to understand. The blue line in the graph represents the probability density function of questions that were not influenced by psychological bias, whereas the red line represents the probability density

Table 3 SVM detecting results.

	Number						
	1	2	3	4	5	6	7
Accuracy	0.44	0.52	0.61	0.64	0.54	0.53	0.44
PPV	0.32	0.49	0.71	0.75	0.49	0.50	0.30
NPV	0.84	0.67	0.50	0.42	0.74	0.67	0.85
Recall	0.55	0.68	0.74	0.74	0.76	0.69	0.51
Specificity	0.40	0.38	0.45	0.41	0.43	0.39	0.39
F1-score	0.33	0.49	0.68	0.71	0.55	0.50	0.32

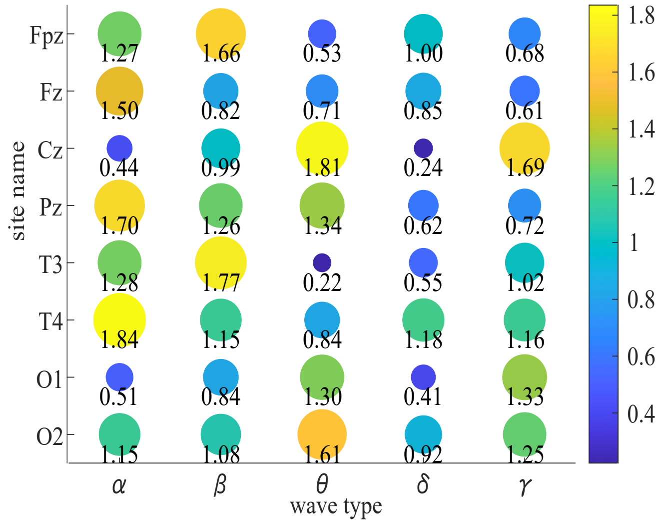

Fig. 3 Result of corresponding importance weight.

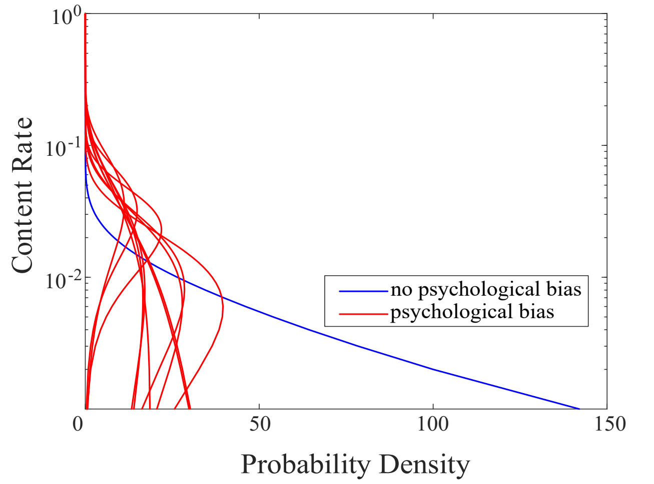

Fig. 4 Probability density functions of the alpha wave at region T4 for the participant with the highest classification accuracy.

function of questions that were influenced by psychological bias. These results visually demonstrate that the distribution parameters differ depending on the presence or absence of psychological bias.

V. Discussion

In this validation experiment, several probability were compared to evaluate their efficacy. Among these, gamma distribution achieved the highesst F1 score. This can be attributed to its flexibility in adjusting the overall shape of the distribution using the shape and scale parameters.

Furthermore, as shown in Fig. 5, the alpha band parameters at T4 exhibited the most significant influence. This may be because T4 is located in the temporal lobe and plays a key role in memory processing. When psychological bias was induced, participants recalled past behaviors stored in their memory to detect their responses.

Next, we considered the causes of misdetections in the proposed method. The NEO-FFI employs a five-point Likert scale, and labels indicating the presence or absence of psychological bias were assigned based on the differences between the two sets of responses. However, the results showed a poor detecting performance for negative (unbiased) cases. This implies that the five-point scale lacks sufficient resolution to detect the presence or absence of psychological bias accurately. Consequently, some responses that were not affected by bias may have been incorrectly labeled as biased.

Additionally, although the proposed method aims to capture the temporal characteristics of brain activity under psychological bias through probability density function fitting, some critical frequency components may appear only briefly and infrequently. In such cases, the characteristics may not have been sufficiently reflected in the content rate distributions, resulting in reduced detecting accuracy.

VI. Conclusions

This study focuses on psychological biases induced during responses to the NEO-FFI and proposes a method to detect the presence or absence of such bias using probability density functions based on the temporal variation in EEG content rates recorded during questionnaire responses.

In a validation experiment involving 23 participants that focused on the neuroticism (N) factor of the NEO-FFI, we used the parameters of a gamma distribution fitted to the content rate dynamics as feature values. The detecting achieved an accuracy of 0.64, positive predictive value (PPV) of 0.75, negative predictive value (NPV) of 0.42, recall of 0.74, specificity of 0.41, and F1 score of 0.71.

In summary, this study demonstrated that probability density functions derived from EEG content rate fluctuations can be used to detect psychological biases during NEO-FFI responses. In future work, incorporating the timing of bias induction, as well as the features observed at those moments may further improve detecting accuracy.

References

[1] Riemann, Rainer, A. Angleitner, and J. Strelau, “Genetic and environmental influences on personality: A study of twins reared together using the self-and peer report NEO-FFI scales,” *Journal of personality*, Vol. 65, No. 3, pp. 449–475, 1997.

[2] N. Archer, R. G. Brown, H. Boothby, C. Foy, H. Nicholas, and S. Lovestone, “The NEO‐FFI is a reliable measure of premorbid personality in patients with probable Alzheimer's disease,” *International Journal of Geriatric Psychiatry: A journal of the psychiatry of late life and allied sciences*, Vol. 21, No. 5, pp. 477–484, 2006.

[3] M. Z. Podolska, M. Bidzan, M. Majkowicz, J. Podolski, O. S. Szmigiel, and E. R. Walknowska, “Personality traits assessed by the NEO Five-Factor Inventory (NEO-FFI) as part of the perinatal depression screening program,” *Medical Science Monitor*, Vol. 16, No. 9, pp. 77–81, 2010.

[4] K. Lee and M. C. Ashton, “Prediction of self-and observer report scores on HEXACO-60 and NEO-FFI scales,” *Journal of Research in Personality*, Vol. 47, No. 5, pp. 668–675, 2013.

[5] S. Sharma, “The Impact of neuroticism and conscientiousness on sleep quality: exploring personality traits and sleep disturbances in young adults,” *International Journal of Interdisciplinary Approaches in Psychology*, Vol. 2, No. 5, pp. 1515–1536, 2024.

[6] D. Peabody and L. R. Goldberg, “Some determinants of factor structures from personality-trait descriptors,” *Journal of personality and social psychology*, Vol. 57, No. 3, p. 552, 1989.

[7] P. T. Costa and R. R. McCrae, “Neo personality inventory-revised (NEO PI-R),” *Psychological Assessment Resources*, 1992.

[8] R. R. Holden and C. E. Lambert, “Response latencies are alive and well for identifying fakers on a self-report personality inventory: A reconsideration of van Hooft and Born 2012,” *Behavior Research Methods*, Vol. 47, pp. 1436–1442, 2015.

[9] S. Horio and K. Takahashi, “Roles of Social Desirability Scales of The Big-Five Personality Inventory in Faking Settings,” *Japanese Association of Industrial/Organization Psychology journal*, Vol. 17, pp. 65–77, 2004.

[10] P. Fossati, S. J. Hevenor, S. J. Graham, C. Grady, M. L. Keightley, F. Craik, and H. Mayberg, “In search of the emotional self: an fMRI study using positive and negative emotional words,” *American Journalof Psychiatry*, Vol. 160, No. 11, pp. 1938–1945.

[11] L. H. Schlochtermeier, L. Kuchinke, C. Pehrs, K. Urton, H. Kappelhoff, and A. M. Jacobs, “Emotional picture and word processing: an fMRI study on effects of stimulus complexity,” *PLoS One*, Vol. 8, No. 2, e55619, 2013.

[12] F. Bermpohl, A. Pascual-Leone, A. Amedi, L. B. Merabet, F. Fregni, N. Gaab, D. Alsop, G. Schlaug, and G. Northoff, “Attentional modulation of emotional stimulus processing: an fMRI study using emotional expectancy,” *Human brain mapping*, Vol. 27, No. 8, pp. 662–677, 2006.

[13] Y. Wang, L. Luo, G. Luan, X. Wang, Q. Wang, and F. Fang, “Rapid processing of invisible fearful faces in the human amygdala,” *Journal of Neuroscience*, Vol. 43, No. 8, pp. 1405–1413, 2023.

[14] A. Öhman, “The role of the amygdala in human fear: automatic detection of threat,” *Psychoneuroendocrinology*, Vol. 30, No. 10, pp. 953–958, 2005.

[15] T. Brosch and M. J. Wieser, “The (non) automaticity of amygdala responses to threat: on the issue of fast signals and slow measures,” *Journal of Neuroscience*, Vol. 31, No. 41, pp. 14451–14452, 2011.

[16] W. Li and A. Keil, "Sensing fear: fast and precise threat evaluation in human sensory cortex," *Trends in cognitive sciences*, Vol. 27, No. 4, pp. 341–352, 2023.

[17] C. Méndez-Bértolo, S. Moratti, R. Toledano, F. Lopez-Sosa, R. Martínez-Alvarez, Y. H. Mah, P. Vuilleumier, A. Gil-Nagel, and B. A. Strange, "A fast pathway for fear in human amygdala," *Nature neuroscience*, Vol. 19, No. 8, pp. 1041–1049, 2016.

[18] R. B. Adams Jr, R. G. Franklin Jr, K. Kveraga, N. Ambady, R. E. Kleck, P. J. Whalen, N. Hadjikhani, and A. J. Nelson, "Amygdala responses to averted vs direct gaze fear vary as a function of presentation speed," *Social Cognitive and Affective Neuroscience*, Vol. 7, No. 5, pp. 568–577, 2012.

[19] K. R. Scherer, M. Costa, P. Ricci-Bitti, and V. A. Ryser, "Scherer, K. R., Costa, M., Ricci-Bitti, P., & Ryser, V. A. (2022). Appraisal bias and emotion dispositions are risk factors for depression and generalized anxiety: Empirical evidence," *Frontiers in Psychology*, Vol. 13, 857419, 2022.

[20] K. R. Scherer, "Evidence for the existence of emotion dispositions and the effects of appraisal bias," *Emotion*, Vol. 21, No. 6, pp. 1224–1238, 2021.

[21] A. B. Brühl, M. Rufer, T. Kaffenberger, V. Baur, and U. Herwig, "Neural circuits associated with positive and negative self-appraisal," *Neuroscience*, Vol. 265, pp. 48–59, 2014.

[22] U. Dannlowski, P. Ohrmann, J. Bauer, H. Kugel, V. Arolt, W. Heindel, A. Kersting, B. T. Baune, and T. Suslow, "Amygdala reactivity to masked negative faces is associated with automatic judgmental bias in major depression: a 3 T fMRI study," *Journal of Psychiatry and Neuroscience*, Vol. 32, No. 6, pp. 423–429.

[23] K. Yamanaka and H. Waki, "Conditional regulation of blood pressure in response to emotional stimuli by the central nucleus of the amygdala in rats," *Frontiers in Physiology*, Vol. 13, 820112, 2022.

[24] L. M. Williams, K. J. Brown, P. Das, W. Boucsein, E. N. Sokolov, M. J. Brammer, G. Olivieri, A. Peduto, and E. Gordon, "The dynamics of cortico-amygdala and autonomic activity over the experimental time course of fear perception," *Cognitive Brain Research*, Vol. 21, No. 1, pp. 114–123, 2004.

[25] C. V. Dayas, K. M. Buller, and T. A. Day, "Neuroendocrine responses to an emotional stressor: evidence for involvement of the medial but not the central amygdala," *European Journal of Neuroscience*, Vol. 11, No. 7, pp. 2312–2322, 1999.

[26] C. S. Inman, K. R. Bijanki, D. I. Bass, R. E. Gross, S. Hamann, and J. T. Willie, "Human amygdala stimulation effects on emotion physiology and emotional experience," *Neuropsychologia*, Vol. 145, 106722, 2020.

[27] J. de Vries, M. Byrne, and E. Kehoe, "Cognitive dissonance induction in everyday life: An fMRI study," *Social Neuroscience*, Vol. 10, No. 3, pp. 268–281, 2015.

[28] S. Kitayama, H. F. Chua, S. Tompson, and S. Han, "Neural mechanisms of dissonance: An fMRI investigation of choice justification," *Neuroimage*, Vol. 69, pp. 206–212, 2013.

[29] G. W. Ploger, J. Dunaway, P. Fournier, and S. Soroka, "The psychophysiological correlates of cognitive dissonance," *Politics and the Life Sciences*, Vol. 40, No. 2, pp. 202–212, 2021.

[30] M. Arsalidou, J. Pascual-Leone, J. Johnson, D. Morris, and M. J. Taylor, "A balancing act of the brain: Activations and deactivations driven by cognitive load," *Brain and behavior*, Vol. 3, No. 3, pp. 273–285, 2013.

[31] Y. Ashikawa, T. Ito, S. Ishizu, and Y. Kurihara, "Detecting of Deliberate Responses due to Social Desirability Bias in Multiple-Choice-Based Personality Tests Using Occipital Lobe EEG Beta Wave Content Rates," 2024 63rd Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE) August, 2024.

[32] Y. Ashikawa, T. Ito, S. Ishizu, and Y. Kurihara, "A method for classification NEO–FFI answers fabricated and advantageous due to psychological bias using brainwave specific brain activity networks," 2024 Asia Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), December, 2024.

[33] Y. Ashikawa and Y. Kurihara, "Proposal for a Method to Classify Fabricated Responses Using a Psychological Bias Loading Model Based on Factor Analysis of EEG During NEO-FFI Responses," 13th IIAE International Conference on Industrial Application Engineering 2025, March, 2025.