Facial Expression and Physiological Analysis of Bluffing in Card Game Psychological Warfare

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Abstract. Facial recognition technology has advanced rapidly, but existing emotion recognition tools assume natural expressions and may not function accurately in strategic situations such as bluffing. This study analyzed facial expressions and physiological responses during a card game involving psychological warfare, using Ekman's Facial Action Coding System (FACS) to identify characteristic Action Unit (AU) patterns. Twelve participants played a bluffing-based card game while their facial expressions and physiological signals were recorded. After each match, participants completed an emotion and strategy questionnaire and annotated their recorded data. The results showed that during bluffing, negative expressions were rare, while smiles (AU12, lip-corner puller; AU6, cheek raiser) appeared frequently, suggesting the possibility of intentional fake laughter. Surprise and smiles often co-occurred in unexpected situations, and confusion was sometimes masked by laughter. Physiological data revealed increases in heart rate and electrodermal activity during bluffing, indicating discrepancies between external expressions and internal states. These findings provide insights into the multimodal detection of bluffing and contribute to the development of affective computing systems for strategic games.

Keywords: card games, psychological warfare, facial expression analysis, FACS, action units, bluffing.

1 Introduction

In recent years, advances in facial expression recognition have led to the use of emotion recognition systems across a variety of fields. In particular, tools such as Azure Face API, OpenFace, and FaceReader make it possible to identify emotions from facial expressions, and applications have progressed in marketing, education, mental health, and security. However, these systems primarily aim to recognize natural expressions, and it has been noted that they do not adequately recognize deliberately manipulated expressions (e.g., bluffing or emotion suppression) (Baltrušaitis, 2019 [1]; Ekman, 2003 [6]).

As a systematic method for analyzing facial expressions, the Facial Action Coding System (FACS) proposed by Ekman and Friesen (1978 [7]; 2002 [8]) is widely used. FACS

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decomposes facial movements into basic components called Action Units (AUs) and is a standard analytical method that identifies emotions from combinations of these AUs. This approach serves as a foundation for detailed analysis of human expressions and emotion inference not only in psychology and physiology, but also in fields such as animation, game development, and medical diagnosis (Bartlett et al., 2014 [2]; Cohn et al., 2007 [3]). However, it does not necessarily cope sufficiently with intentional manipulation of expressions in situations such as psychological warfare.

In situations involving psychological warfare, such as poker and negotiation, players conceal emotions or, conversely, use deceptive expressions (bluffs). According to Ekman (1982 [5]), emotions are expressed through specific AUs, but in psychological warfare the manipulation of expressions may alter the frequency and combinations of these AUs. Furthermore, Pentland (2010 [16]) points out that nonverbal signals play an important role in social interaction, indicating that analyzing expression manipulation in psychological warfare requires approaches that go beyond conventional emotion recognition methods.

In this study, we aim to clarify characteristic patterns during bluffing by analyzing facial expression data and physiological information (heart rate) in psychological warfare. Specifically, we will:

1. Collect players' facial expressions and physiological information through experiments involving a card game with psychological warfare.
2. Use FACS to analyze AU occurrence frequencies during emotions and bluffing, and identify characteristic patterns.
3. Statistically analyze heart rate data to examine changes in physiological responses during bluffing.
4. Analyze correlations between facial expressions and physiological information to obtain foundational insights toward automatic detection of bluffing.

The outcomes of this study may be applicable to the automatic detection of bluffing in the field of affective computing. For example, as an assistive system for card games, real-time analysis of players' psychological states could enable new forms of strategic support. In this paper, we first review related work and then describe the experimental methods in detail. We subsequently present the experimental results and discuss them. Finally, we state the conclusions of this study and outline future prospects.

1.1 Facial Expression Recognition and Psychological Warfare

Many studies on facial expression recognition target natural emotional expressions, and research analyzing intentionally manipulated expressions (e.g., bluffs or concealed emotions) remains limited (Matsumoto & Hwang, 2011 [13]; Frank & Svetieva, 2014 [14]). In situations involving psychological warfare, it is common for players to deliberately manipulate their expressions to deceive opponents, and previous studies have reported that the accuracy of deception detection is generally low (Bond & DePaulo, 2006 [9]; Salem & Sumi, 2024 [10]).

In interpersonal games such as poker, the influence of facial and other nonverbal cues on players' strategies has drawn attention, and some studies have conducted analyses based on FACS (Bond & DePaulo, 2006 [9]). These studies suggest that players intentionally manipulate expressions—using positive expressions (smiles) to deceive opponents and, conversely, suppressing negative expressions (confusion, tension). However, attempts to integrate and analyze not only facial expressions but also physiological data (such as heart rate and electrodermal activity) remain scarce.

1.2 Physiological Information and Psychological States

In emotion recognition, the measurement of physiological information plays an important role alongside changes in facial expressions. In particular, heart rate (HR) and electrodermal activity (EDA) are often used as indicators of emotional and stress states (Kreibig, 2010 [11]). Previous studies have reported marked changes in heart rate and electrodermal activity with increases in tension and stress (Meijer et al., 2016 [20]). Conversely, in situations where emotions are intentionally concealed, such as bluffing, a gap may arise between facial expressions and physiological information. For example, even if a positive facial expression like a smile is displayed, increases in heart rate or EDA may be interpreted as signs of deception (Salem & Sumi, 2024 [10]). By analyzing such discrepancies between expressions and physiological responses, it is expected that the accuracy of bluff detection can be improved.

1.3 Positioning within Affective Computing

Affective computing is a research field in which computers aim to understand human emotions and respond appropriately (Picard, 1997 [17]), and emotion recognition technology is a central element of it (Bond & DePaulo, 2006 [9]). Conventional emotion recognition systems have focused on classifying general emotional states (joy, anger, surprise, etc.), but they have not sufficiently addressed situations in which emotions are intentionally manipulated, such as psychological warfare. An integrated analysis of the characteristics of facial expressions and physiological information in psychological warfare, as conducted in this study, represents an important contribution to the domain of affective computing. In particular, to detect deceptive expressions such as bluffs, multimodal analyses that combine facial expression recognition with physiological data are considered effective. The outcomes of this study may lead to the development of real-time emotion analysis systems and strategy-support systems for interpersonal games.

1.4 Attempts at Bluff Detection

In recent years, the field of affective computing has seen progress in research on bluff detection. Studies leveraging machine learning attempt to identify deception by analyzing subtle changes in facial expressions (micro-expressions) and patterns in physiological information (Deng, Zhang, & Fu, 2019 [4]). Moreover, recent research using deep learning has shown promising results in pattern recognition for facial expressions and physiological signals (Rouast, Adam, & Chiong, 2019 [12]). However, there are relatively few existing studies that integratively analyze facial expressions and physiological information in the context of psychological warfare. By combining AU analysis based on FACS with the measurement of physiological information, this study aims to clarify the characteristics of bluffing in psychological warfare and to pave the way for applications to future automatic recognition systems.

2 Experimental Systems

In order to investigate the relationship between facial expressions, physiological responses, and bluffing behaviors in psychological warfare, we constructed an experimental system consisting of three components: (1) a facial expression recognition system, (2) an emotion/bluff annotation tool, and (3) a physiological signal recording platform. In addition, we designed a card game task that naturally induces situations involving bluffing, and administered questionnaires to evaluate participants' traits and subjective experiences. The following subsections describe each component in detail.

2.1 Facial Expression Recognition System

For the automatic recognition of facial expressions, we employed **OpenFace** (Baltrušaitis, 2019 [1]), an open-source toolkit for facial behavior analysis developed by Tadas Baltrušaitis in collaboration with the MultiComp Lab. OpenFace has been widely adopted in domains such as facial expression analysis and gaze tracking, owing to its capability to process live camera streams, still images, and video recordings. The system extracts 68 facial landmarks across key regions (e.g., eyes, mouth, nose, eyebrows, jaw), estimates head pose, detects 17 distinct Action Units (AUs), and measures gaze direction. This enabled us to obtain detailed and objective data on participants' facial movements during gameplay.

2.2 Emotion and Bluff Annotation Tool

In this study, we used an annotation tool to record the emotions felt by participants during matches as well as instances of facial disguise (bluffing). This tool (Tiam-Lee & Sumi, 2018 [18]; 2019 [19]) was designed to allow participants to intuitively label emotions or bluffs while viewing the recorded footage. Two types of annotation interfaces were provided: one for labeling "emotions" and another for labeling "bluffs." For each interface, participants clicked the corresponding button (e.g., joy, surprise, confusion, tension), which placed an arrow on the timeline. They could then drag to adjust the relevant time range. This design enabled participants to more accurately document the emotions they experienced and the moments in which bluffing occurred. The annotated data were saved in JSON format, including information such as the video file name, total playback duration, start and end times of each annotation, the type of emotion or bluff, and a label ID for identification within the tool.

2.3 Physiological Signal Recording Platform

To acquire heart rate data during gameplay, we employed **OpenSignals** in conjunction with the BITalino biosensor platform. OpenSignals is a software package that enables real-time visualization and recording of physiological data. In this study, the BITalino device was connected to a personal computer via Bluetooth, with sensors appropriately positioned for the type of data collected. Heart rate was continuously monitored as a physiological indicator of emotional state. By examining the relationship between facial expression changes and physiological responses, we aimed to obtain a more comprehensive understanding of participants' affective reactions during psychological warfare.

2.4 Card Game Employed

The experimental task involved a rock-paper-scissors-based card game, originally developed by Yuta Nisiguchi (2020 [15]). The deck consisted of cards representing "rock," "scissors," or "paper," each assigned a score from 1 to 10, with each card type appearing twice, resulting in a total of 60 cards.

The selection of this game was based on two main considerations. First, because the rules follow the familiar framework of rock-paper-scissors, participants could quickly understand the mechanics. This minimized the cognitive load of rule acquisition and allowed them to focus more on strategic and psychological engagement. Second, the game inherently encouraged strategic interaction: since all players' hands remained visible, participants constantly had access to their opponents' potential actions. This transparency required predictive reasoning and fostered deceptive tactics, such as bluffing.

For experimental control, four predetermined sets of hands were prepared in advance. This ensured that all participants encountered identical scenarios, thereby eliminating randomness as a factor and enhancing fairness. The details of these prepared hands are shown in Table 1, which illustrates the composition of hands used in each match. By standardizing the gameplay situations, players were compelled to infer opponents' intentions, thus increasing opportunities for psychological warfare and bluffing.

Table 1. Composition of hands prepared for each match.
(The number following each hand indicates the score assigned to that card)

Match	Player	Card 1	Card 2	Card 3	Card 4
1st match	First	paper,3	rock,5	scissors,7	None
	Second	paper,3	rock,5	scissors,7	None
2nd match	First	rock,3	scissors,5	paper,7	None
	Second	rock,7	scissors,5	paper,3	None
3rd match	First	rock,2	rock,3	paper,4	None
	Second	rock,4	rock,5	scissors,9	None
4th match	First	paper,4	scissors,3	scissors,3	rock,9
	Second	paper,7	scissors,4	scissors,4	rock,6

2.5 Questionnaire Used in the Experiment

Participants completed three sets of questionnaires during the study.
First, prior to the experiment, they provided demographic information (e.g., age, gender), background related to card game experience, and self-assessments regarding bluffing skills, facial expression control, and recognition of others' expressions. These data served to establish a baseline for individual differences.
Second, personality traits were assessed using the Japanese version of the Ten-Item Personality Inventory (TIPI-J) (Oshio & Abe, 2012 [21]). This instrument evaluates the Big Five personality dimensions, extraversion, agreeableness, conscientiousness, neuroticism, and openness, on a five-point Likert scale.
Finally, after completing the experimental matches, participants responded to a post-experiment questionnaire. This included items on their use of facial expressions as a strategic tool, perceptions of the rules' complexity, and subjective experiences of psychological warfare. In addition, participants were invited to provide free-form comments, which offered qualitative insights into their experiences.

3 Experiment

This chapter describes the experimental design, setup, and procedures used to collect and analyze participants' facial expressions, physiological responses, and bluff-related behaviors during gameplay.

3.1 Experimental Setup

As illustrated in Figure 2, two participants were seated facing each other across a table to engage in the card game. At the center of the table, a box with a height of 40 cm was placed, to which two webcams were mounted, one directed at each participant, for the purpose of recording their facial expressions. In addition, an additional webcam was positioned in front of the table to capture the overall scene, including both participants and the playing area. The cameras mounted on the central box were connected to the personal computers (PCs) assigned to each participant, enabling real-time recording of the captured video directly onto the respective PCs. The front-facing camera was connected to the experimenter's PC and was used to record the overall progress of the game. This configuration allowed for the simultaneous acquisition of both individual-level data for each participant and contextual data of the entire session. A whiteboard was placed on the table to record scores during gameplay. Participants could freely update the scores, which facilitated monitoring of the match's progress. For tasks requiring concentration, such as completing questionnaires or labeling emotions, partition panels were installed between participants. These partitions prevented visual contact between participants, thereby minimizing distractions and ensuring that each individual could focus on the assigned tasks without interference. To synchronize all recorded video streams, a clock was positioned within the camera's field of view. This facilitated temporal alignment of the data during post-experimental analysis. Each participant's PC displayed the video feed from the camera directed at them, and a Word document containing the experimental procedure and relevant instructions was kept open on the desktop. This arrangement ensured that participants could proceed with the experiment smoothly and without confusion. Overall, the experimental environment was designed to capture data from multiple perspectives, enabling detailed documentation of both facial expressions and behavioral changes exhibited by participants throughout the session.

3.2 Experimental Procedure

The primary objective of this experiment was to collect and analyze participants' facial expression and emotional data through a card game incorporating elements of psychological deception. The detailed procedure is described as follows.

Initially, participants were provided with a verbal explanation of the experiment's objectives, procedures, data usage policies, and ethical considerations. Written informed consent was then obtained. Following this, participants completed a pre-experiment questionnaire. Subsequently, the experimental environment was prepared. Camera positions were adjusted to ensure that each participant's face remained consistently within the frame. A clock, visible to participants and within the camera's field of view, was positioned to facilitate temporal synchronization of recorded data; while it was not required to be constantly visible, it was placed such that participants could refer to it when necessary. Participants were then equipped with a biosensor designed to measure heart rate during the session. Prior to attachment, instructions regarding proper handling and placement were provided, and participants followed a reference manual to ensure correct setup. Once preparation was complete, the main phase—the card game—was conducted. Before gameplay began, participants were explicitly instructed to actively engage in bluffing (deliberate deception) during matches. A total of four matches were played, each recorded by the installed cameras.

The rules for each match were as follows:

Distribute hands to each participant; all cards must be visible to both players.

The first player selects a card and places it face-down.

The second player asks a question to the first player, who may choose to answer truthfully or deceptively.

The second player then selects a card and places it face-down.

Both players reveal their cards simultaneously. The winner earns the number of points indicated on their played card, and the revealed cards are discarded.

Steps 2–5 are repeated until no cards remain.

After each match, participants completed a questionnaire regarding their emotional state and self-assessment of their psychological strategies during gameplay. They then performed an annotation task on the recorded video data. Using the "Emotion Tool.html" and "Bluff Tool.html" applications located in the stream-annotator-tool-master/demo directory, participants annotated time points at which specific emotions or bluff-related expressions occurred. The resulting annotation files were saved as result.json, renamed according to the match number and participant ID (e.g., 3-no11.json for the third match of participant 11), and stored in their respective "Emotion" or "Bluff" folders. Upon completion of all matches, participants were asked to respond to a post-experiment questionnaire, which included open-ended questions on overall impressions of the experiment as well as self-evaluations of their psychological state during gameplay. Additional supplementary questions were posed as needed. Finally, participants were compensated in cash, marking the conclusion of the experiment.

3.3 Weighted Mean Analysis of AU Data Based on Labeled Time Ranges for Each Subject's CSV File (Python)

This study analyzed Action Unit (AU) data from experimental CSV files, calculating mean AU values within labeled time ranges. The analysis produced (1) mean AU values for each label ID, (2) overall means across the entire match, and (3) ratios of label-specific AU values relative to the overall mean.
The procedure was as follows: CSV and JSON files were organized by subject ID. From each CSV, only successful frames were extracted, and AU columns were obtained; JSON files provided label start and end times. AU data within each labeled range were aggregated, and identical labels were merged using weighted means. The overall AU frequency was then calculated as a baseline, and label-specific AU values were expressed as ratios to this mean.
Results were saved as per-subject CSV files, including AU values and ratios for each label ID and "Overall Mean." Finally, average AU ratios per label were computed across all subjects.

4 Results

This chapter presents the findings of the experiment. The results are organized into four parts: questionnaire responses collected before, during, and after the matches; facial expression data analysis; physiological data analysis; and the relationship between facial expressions and physiological responses.

4.1 Questionnaire Results

The pre-experiment questionnaire asked about participants' demographic information, experience with card games, and self-evaluations of abilities relevant to psychological warfare. Regarding card game experience, poker was the most frequently mentioned genre, followed by trading card games such as Shadowverse and Evolve, and memory-type games such as Concentration. This shows that while some participants were accustomed to competitive strategic games, others had experience with simpler forms of card play. In terms of skill at deception, none of the participants rated themselves as particularly good at bluffing. About half judged themselves to be "somewhat good," whereas more than two-fifths admitted that they were poor at deceiving others, and one participant rated themselves slightly below average. This indicates that bluffing was not a strong self-assessed skill for many participants. With respect to facial expression control, two-thirds of the participants felt they were somewhat good at intentionally producing facial expressions, and none rated themselves as poor in this ability. A similar trend was observed for reading others' expressions, where two-thirds considered themselves somewhat capable and one participant rated themselves as good. Finally, almost all participants—more than ninety percent—recognized the importance of facial expressions in psychological warfare, with the majority rating them as very important. These findings suggest that although participants valued facial expressions as a key factor, their self-perceived abilities in bluffing and expression control varied considerably..

In the post-match questionnaire, we investigated how players experienced psychological warfare, the success rate of bluffs, and the influence of the opponent's facial expressions.

(1) Bluff success rate and facial expression control

When players who attempted a bluff were asked "Were you able to maintain a neutral façade?", 74% (23 participants) answered "yes," and 26% (8 participants) answered "no" (Table 2). These results suggest that although many participants felt they successfully bluffed, approximately one-quarter may have failed to control their expressions and were potentially seen through by their opponents.

In response to the question "Did you feel that your opponent was lying?", 33% (16 participants) answered "yes," and 67% (32 participants) answered "no" (Table 2). This indicates that accurately detecting an opponent's bluff in psychological warfare is not easy.

(2) Effect of questioning and tension in psychological warfare

Among players who asked questions during the match, 52% (15 participants) felt that their questions were effective, while 48% (14 participants) felt they were not (Table 7). In response to the question "Did you feel nervous when being questioned?", 48% (14 participants) answered "yes," and 42% (10 participants) answered "no" (Table 2).

These results suggest that the effectiveness of questioning in psychological warfare is case-dependent, and being questioned does not necessarily induce tension in all players.

(3) Perceived psychological advantage

In response to the question "Did you feel you were in a superior position to your opponent?", 44% (21 participants) answered "yes," while 56% (27 participants) answered "no" (Table 2). This indicates that many players did not strongly feel psychologically superior during the match. This tendency suggests that psychological warfare involves balanced strategic elements in which players mutually anticipate each other's moves.

Table 2. Results of the post-match survey (Q4–Q11).

Question	Response: Yes	Response: No
Q4 (When you lied, were you able to pretend to be normal?)	23(74%)	8(26%)
Q5(Do you think your question was effective?)	15(52%)	14(48%)
Q6(Are you nervous when asked?)	14(48%)	10(42%)
Q7(Did you answer the question right away?)	15(63%)	9(37%)
Q8(Did you answer the question with confidence?)	18(75%)	6(25%)
Q9(Did you feel that the other person was lying?)	16(33%)	32(67%)
Q10(Were you able to guess your opponent's move?)	24(50%)	24(50%)

Q11(Did you feel like you had an advantage over your opponent?)	21(44%)	27(56%)

4.1.1 Post-Experiment Questionnaire Results

Following the completion of all experimental sessions, participants were asked to complete a questionnaire assessing the perceived difficulty of engaging in psychological tactics and the extent to which facial expressions influenced match outcomes.

1. **Influence of facial expressions on match outcomes**
   In response to the question *"Did you use facial expressions to win the game?"*, 41.7% of participants selected the highest rating ("very much"), while 25% chose "not at all" and another 25% chose "2" on the 4-point scale. These results indicate that while some participants felt strongly that facial expressions contributed to their victory, others perceived little to no impact.
2. **Perceived difficulty of the game rules**
   When asked *"Were the rules of the card game complicated?"*, half of the participants (50%) rated them as "not at all," and 33.3% as "2." Only a small number found the rules somewhat or very complicated. This suggests that the rules were generally considered easy to understand, allowing players to focus on psychological tactics.
3. **Frequency of psychological tactics**
   In response to the question *"Did you feel that psychological warfare had occurred?"*, 58.3% selected "very much," while none chose "not at all." This indicates that the majority of participants perceived psychological tactics to be present during the matches.

Table 3. Post-experiment questionnaire (Q1–Q3) response results.

Question content	1 (Not at all)	2	3	4 (Very much)
Q1. Did you use facial expressions to win the game?	3 (25%)	3 (25%)	1 (8.3%)	5 (41.7%)
Q2. Were the rules of the card game complicated?	6 (50%)	4 (33.3%)	1 (8.3%)	1 (8.3%)
Q3. Did you feel that psychological warfare had occurred?	0 (0%)	2 (16.7%)	3 (25%)	7 (58.3%)

4.2 Facial Expression Data Analysis Results

Figure 1 shows the AU frequency ratio for bluffing. The ratio was calculated by setting each participant's average AU occurrence frequency across all games to 1 and then computing the AU frequency ratio for each label.

The analysis revealed that the frequency of certain AUs (e.g., AU12, AU6) tended to be higher during bluffing and during expressions of joy (Figure 2a). In particular, AU12 (lip corner puller) and AU6 (cheek raiser) appeared frequently, suggesting that expressions conveying positive impressions may be strategically used in psychological warfare. On the other hand, AU4 (brow lowerer) tended to increase during periods of tension (Figure 3b). Distinct AU patterns were also observed for surprise and confusion (Figure 2b, Figure 3a).

Furthermore, a t-test confirmed that AU12 and AU6 appeared significantly more frequently during bluffing and joyful expressions. Figure 4 shows the relationship between AU12 frequency and heart rate, indicating a trend that smiling expressions may accompany physiological arousal. These results suggest that the deliberate use of positive-looking expressions, sometimes mismatched with physiological states, may function as a strategic tool in psychological warfare.

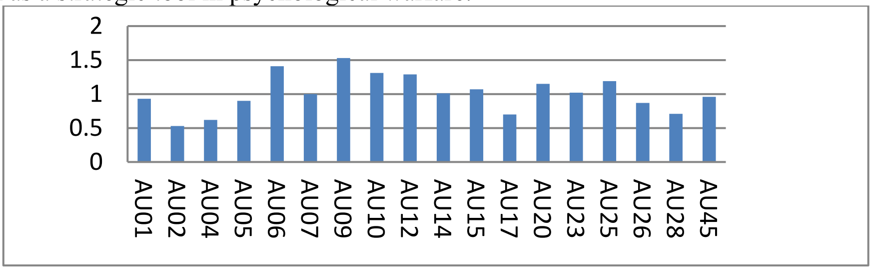

Fig. 1. AU frequency ratio during bluffing (LabelID5)

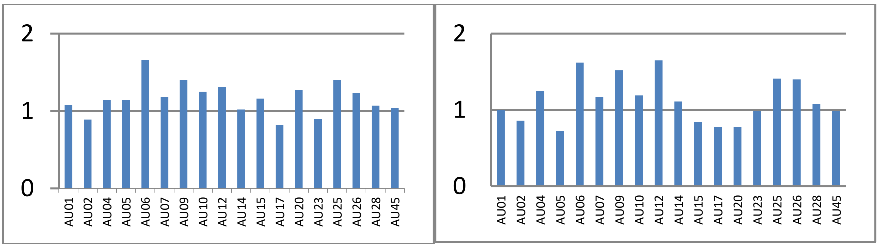

Fig. 2. AU frequency ratios for (a) joy (LabelID1) and (b) surprise (LabelID2)

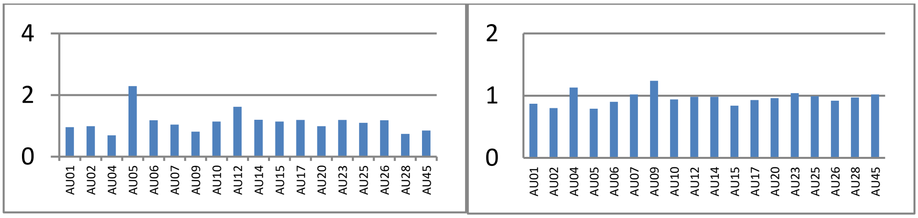

Fig. 3. AU frequency ratios for (a) confusion (LabelID3) and (b) tension (LabelID4)

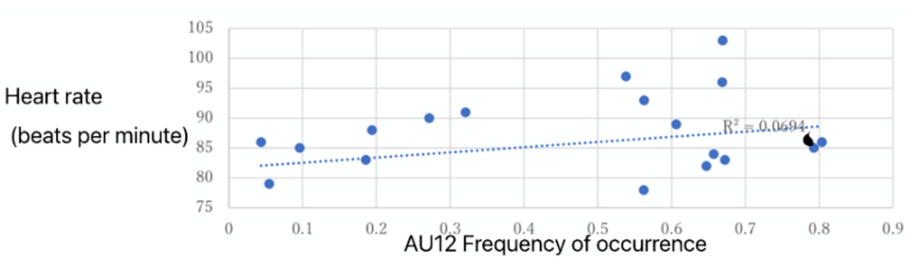

Fig. 4. Relationship between the frequency of AU12 and heart rate

4.3 Physiological Data Analysis Results

Physiological measurements of heart rate provided additional insights. On average, heart rate was slightly higher during bluffing than during normal play, though the difference was not statistically significant. More importantly, heart rate variability was smaller during bluffing, suggesting that under the stress of deception, heart rate responses converged within a narrower range. By contrast, in normal play, individual differences in relaxation and concentration led to wider variability. Taken together, these findings indicate that heart rate alone is insufficient to reliably distinguish bluffing situations.

5 Discussion

In this chapter, based on the experimental results, we consider the characteristics of facial expressions and biological information in psychological warfare, and discuss the relationship between facial expressions and physiological responses when bluffing, the manipulation of facial expressions as a psychological warfare strategy, and the significance of this research and future challenges.
We also examined the relationship between facial expressions and physiological responses. No significant correlation was found between the frequency of AU12 (smiling) and increases in heart rate, nor between bluffing expressions and physiological responses. The lack of statistical significance is likely due to the limited sample size. Nevertheless, the observed trends suggest that players may deliberately display positive expressions while internally experiencing tension.

Future research should therefore collect data from larger samples and incorporate additional physiological measures such as electrodermal activity, EEG, or eye-tracking, to improve the accuracy of bluff detection in psychological warfare.

5.1 Features of Facial Expressions and Physiological Responses During Bluffing

From the experimental results, it was confirmed that specific facial expression patterns occur at high frequency during bluffing in psychological warfare. In particular, AU12 (lip corner puller) and AU6 (cheek raiser) appeared significantly more often during bluffing. Because these movements are generally closely associated with positive emotions such as joy (Ekman, 1982 [5]; Ekman, 2003 [6]), this suggests that players intentionally attempt to project a positive impression.

Meanwhile, analysis of physiological data showed a tendency for heart rate (HR) to increase during bluffing, but the difference was not statistically significant. Previous studies have also reported that physiological measures such as HR and EDA are sensitive to stress and tension (Kreibig, 2010 [11]; Meijer et al., 2016 [20]). These results indicate that players often manipulate their expressions while concealing internal tension. In particular, discrepancies between facial expressions and physiological responses may be an important factor in identifying bluffs (Bond & DePaulo, 2006 [9]).

5.2 Manipulation of Facial Expressions as a Strategy in Psychological Warfare

To successfully bluff, players are required to produce expressions that convey trust and reassurance. In this study, AU12 (smile) and AU6 (cheek raiser) were found to be frequently used during bluffing, suggesting that players may employ forced smiles to deceive opponents. This aligns with prior findings that smiles can be strategically used to mask negative emotions (Matsumoto & Hwang, 2011 [13]; Frank & Svetieva, 2014 [14]).

In addition, AU25 (lips part) and AU26 (jaw drop), which indicate surprise, were observed with a certain frequency, possibly as performative elements to make opponents think that an "unexpected development" was occurring. Furthermore, in scenes labeled as confusion, AU12 (smile) was frequently observed, suggesting that masking confusion with a smile may also be used in psychological warfare.

Conversely, AU9 (nose wrinkler) and AU4 (brow lowerer), which indicate tension, were relatively suppressed. This suggests that players deliberately inhibit negative emotions so as not to provide cues to their opponents, consistent with theories that nonverbal signals can be strategically controlled in social interactions (Pentland, 2010 [16]).

5.3 Significance of This Study and Future Issues

This study is significant in that it quantitatively clarified the manipulation of facial expressions in psychological warfare. By demonstrating the relationship between facial expression patterns and physiological responses, future applications can be expected in bluff detection and emotion recognition systems.

First, bluff detection systems may be constructed by combining AU analysis with physiological measures such as electrodermal activity (EDA). For example, detecting a player who displays a positive expression while showing signs of tension could support real-time bluff identification. Machine learning approaches tailored to psychological warfare scenarios may further enhance such systems, with applications in competitive games such as poker (Deng, Zhang, & Fu, 2019 [4]) and in support tools for negotiations.

Second, the experimental design should be improved by increasing the number of participants. The present study involved only 12 participants, which limits generalizability. Considering individual differences such as personality traits and prior experience is also important. In particular, analyzing the relationship between Big Five personality traits and expression manipulation could clarify tendencies based on individual characteristics (Oshio & Abe, 2012 [21]).

Finally, future studies should incorporate additional physiological measures such as EEG, EMG, and EDA, as well as eye-tracking, to achieve a more comprehensive understanding of players' psychological states and strategies. Such multimodal analyses are in line with the broader objectives of affective computing (Picard, 1997 [17]; Rouast, Adam, & Chiong, 2019 [12]). Nevertheless, the limited number of participants (n = 12) remains a major limitation of this study. This constraint reflects its exploratory nature, and future work should include a larger and more diverse sample to improve reliability and generalizability.

6 Conclusion

This study examined the characteristics of facial expressions and physiological responses in psychological warfare, focusing on bluffing behavior. The key findings are as follows:

- During bluffing, AU12 (smile) and AU6 (cheek raiser) appeared significantly more often, indicating the strategic use of positive expressions.
- Players intentionally manipulated facial expressions, such as feigned smiles or surprise, to deceive their opponents.
- Discrepancies between facial expressions and physiological responses, particularly heart rate, emerged as potential indicators for bluff detection.

These results suggest that bluff detection systems can be enhanced by combining facial expression analysis with physiological data. Future work will expand the participant pool, integrate additional physiological measures (e.g., EDA, EEG), and improve the accuracy of bluff classification models through machine learning approaches.

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