

VIETNAMESE-FOCUSED COLOR-BASED MODELS FOR DYADS EXPRESSING FOR ROBOTS

DAO THANH HUYEN^{1,2}, NGHIA THI MAI^{2,*}, SUZUKA TANAKA¹
KOTARO HASHIKURA¹, MD ABDUS SAMAD KAMAL¹, IWANORI MURAKAMI¹
AND KOU YAMADA¹

¹Graduate School of Science and Technology
Gunma University
1-5-1 Tenjincho, Kiryu 376-8515, Japan
{ t231b054; t232b607; k-hashikura; maskamal; murakami; yamada }@gunma-u.ac.jp

²Faculty of Electronics Engineering 1
Posts and Telecommunications Institute of Technology
122 Hoang Quoc Viet Road, Cau Giay District, Hanoi 11355, Vietnam
huyendt@ptit.edu.vn; *Corresponding author: nghiamt@ptit.edu.vn

Received June 2024; revised October 2024

ABSTRACT. *Robots capable of human communication play crucial roles in various daily tasks, particularly in nursing and mental healthcare. Effective emotion expression is essential for robots to perform these tasks proficiently. However, prior methods for robot emotion expression often involve complex designs, making them costly and impractical for widespread application. Additionally, color-based methods for emotional expression have not been thoroughly explored within the Vietnamese cultural context, where nuances in color interpretation are significant. This study is the first to specifically investigate cultural differences in emotional expression for robots using colors and gradients tailored to Vietnamese demographics. Moreover, we propose a simple, cost-effective design for robot emotion expression that addresses the shortcomings of previous approaches, which rely on complex and expensive designs, while still being capable of expressing complicated emotions such as dyads. Experimental results demonstrate the effectiveness of these models in conveying extended emotional states and dyads, independent of traditional human-like expressions. These findings underscore the practical potential of such models, particularly within Vietnamese nursing and mental healthcare sectors.*

Keywords: Robot, Emotion, LED, Color, Gradation

1. Introduction. Individuals with social anxiety tend to find it easier to interact with robots, especially those with a metallic body, than with humans, underscoring a unique application of robotic technology [1]. This observation has led to a notable surge in interest in partner robots in recent years. Consequently, research has delved into the utilization of robots for counselling purposes [2], as well as the creation of robotic companions aimed at enhancing the mental well-being of the elderly. Such robots are viewed as potential substitutes for traditional human caregivers, addressing both companionship and care requirements [3, 4].

This shift signifies a growing demand for emotional support from robots, in addition to physical assistance. Meeting this need requires robots to extend beyond their physical capabilities to include emotional and communicative functions. Effective communication with humans necessitates robots not only understanding human behavior but also expressing emotions – a crucial aspect of natural human interaction. The capability of robots

to convey emotions is deemed essential for fostering more predictable and relatable interactions with humans, ultimately enhancing human-robot interaction. This progress is anticipated to result in more meaningful and effective interactions between humans and robots, bridging the gap between technological capabilities and human social needs [5].

While it is recognized that robots should possess the ability to express emotions, the intricacy of most emotion expression mechanisms presents a challenge. These mechanisms encompass various aspects such as facial expressions, body language, gestures, and speech prosody. The high cost and complexity of current multi-modal systems indicate the need for simpler robot designs. Studies have shown that these systems, while capable of conveying emotions, are resource-intensive and often prohibitively expensive, making them impractical for widespread real-world application, especially in industries like nursing and mental healthcare. For instance, [6] has shown that facial emotion recognition systems used in Human-Robot Interaction (HRI) require high-end processing capabilities and advanced sensors, leading to increased costs and maintenance requirements. The complexity of such systems often makes them prone to errors in uncontrolled environments, further reducing their scalability. Meanwhile, [7] highlighted that deep learning models used for real-time emotion recognition in robots can achieve high accuracy, but only under controlled conditions, and they struggle with accuracy in dynamic, real-world environments. In contrast, simpler designs – such as using color-based emotional expressions – eliminate the need for costly hardware while still effectively communicating a broad range of emotions. Studies have demonstrated that non-verbal cues like color are effective in conveying emotions and are significantly less resource-intensive [8, 9]. A substantial body of research [10, 11, 12, 13] supports the idea that colors inherently convey emotions and feelings, suggesting color as a more straightforward means for robots to express emotions [5, 14, 15, 16, 17]. These studies indicate that by utilizing color, we can transform complex robots into affordable mental companions, potentially aiding in the treatment of mental health patients. By focusing on a more streamlined approach, our research aims to create robots that are cost-effective, easy to maintain, and scalable for large-scale use in real-world applications, particularly in healthcare settings where reliability and affordability are critical.

However, two primary issues need consideration. Firstly, prior research predominantly focuses on basic emotions, while there are still 24 extended emotions and additional dyads [18]. Developing models to express these extended emotions and dyads could enhance robots' human-likeness. They would be able to convey subtle emotional nuances, fostering greater comfort in communication and enhancing the overall human-machine interaction experience.

The second concern relates to the cultural diversity in the interpretation of colors [19, 20]. [19] highlights the varied cultural meanings attributed to yellow, ranging from envy in Germanic cultures to purity and royalty in Chinese, and to happiness in Korean contexts. The significance of white varies across cultures, highlighting the complexity of color symbolism. In Japan, white symbolizes purity, cleanliness, and is commonly associated with weddings and traditional aesthetics. However, in Vietnam, white is predominantly linked to mourning and death, representing purity and spirituality but with a strong association with mortality. These differences are critical in the realm of emotional expression for robots, as color can significantly influence human perception and response. In human-machine interactions, the incorrect use of color to express emotions could lead to misunderstandings, misinterpretations, and ineffective communication. For instance, using the color white to represent a positive emotion in Vietnamese culture could lead to confusion, as white is traditionally associated with mourning and death. Thus, cultural

sensitivity in color interpretation is crucial for ensuring robots can communicate emotional states accurately and effectively across different cultural contexts. Misunderstandings could not only reduce the effectiveness of the robot's emotional expression but also harm the trust and engagement between humans and machines. These cultural differences underscore the need for research in this area, especially in countries like Vietnam, which have significant potential for the deployment of mental health robots due to their large population exceeding 100 million. Despite this potential, there seems to be a lack of investigation into color-based emotional expression models tailored to the Vietnamese context, suggesting a promising avenue for future research that could improve the development of culturally sensitive robots capable of emotional communication.

Moreover, existing research on color-based emotional expression in robots has predominantly concentrated on populations outside of Vietnam [17, 21], prompting concerns regarding the applicability of these models to diverse cultural contexts. This gap highlights the necessity of assessing these models with Vietnamese participants to verify their effectiveness and appropriateness. Such validation is crucial for laying the groundwork for future advancements in this domain.

As robots are increasingly deployed worldwide, adapting emotional expression models to encompass a broader range of emotional and cultural nuances can greatly enhance their practicality and acceptance in real-world settings. Customizing these models to incorporate extended emotions and dyads, beginning with research in Vietnam, is vital for the development of robotic companions that are empathetic and culturally attuned.

With the aforementioned motivations in mind, our research aims to investigate the effectiveness of two models utilizing color to convey emotions and dyadic expressions. Specifically, we explore two robotic emotional expression models:

- 1) Color with blinking features for extended emotions;
- 2) A model for expressing primary dyads through a two-color gradient approach.

These models are presented to research survey participants, and the gathered data undergoes comprehensive analysis to assess the insights and effectiveness of the models. Our research encompasses 170 participants, with each experiment engaging a unique, non-overlapping participant group to ensure the validity and generalizability of our findings.

Our preliminary findings suggest that the approaches are effective in conveying extended emotional states and dyads to some extent, without relying solely on traditional human-like expressions. However, due to the intricate and subjective nature of color interpretations within the Vietnamese cultural context, there is potential for further improvement in the models. This observation highlights the importance of conducting thorough research into the role of color in Vietnamese communication, particularly concerning extended emotions and dyadic expression, to develop a more precise and culturally sensitive color model for robotic applications. Our research aims to deepen understanding of how Vietnamese individuals interpret colors in practical contexts, laying the groundwork for future investigations into specialized color-based models for emotion and dyadic expression tailored to Vietnamese culture. The organization of this paper is as follows. Section 2 reviews some related works. Section 3 introduces the extended emotions and their combinations as dyads in the context of our research. Section 4 presents details on the models utilized for expressing emotions and dyads through colors. The methodology, including the experimental design and procedures, is outlined in Section 5. Findings from the experimental phase are summarized in Section 6. A discussion of these results, their implications, and insights derived from them are provided in Section 7. Section 8 discusses some potential directions for future research in this domain. The paper concludes with Section 9, offering final thoughts and observations.

2. Related Works. Various methods exist for linking emotions with colors, with Plutchik’s framework [18] standing out as one of the most prominent. Plutchik’s research illustrated that colors could represent basic emotions and, when blended, convey more nuanced feelings. Initially, the author identified eight primary emotions: joy, acceptance (later renamed trust [22]), fear, surprise, sadness, disgust, anger, and anticipation. By assigning three levels of intensity to each emotion, a total of 24 extended emotions were derived based on their fundamental emotion and intensity. Additionally, Plutchik introduced the concept of a dyad, representing the combination of two primary emotions, to capture more complex emotional states.

Numerous studies have investigated the use of colors to convey emotions in robots [14, 15, 16, 17, 21]. Sugano and Ogata [14] developed a method where a robot’s head color, along with other expressions, conveyed emotions such as fear (blue), anger (red), and joy/anticipation (yellow). [15] introduced a technique involving head and cheek colors, combined with facial expressions, to express emotions like anger (red head) and joy (green head). However, their approach supplemented colors with other expression methods and lacked diversity in emotional range. [16] used a robot named Nao to depict eight basic emotions through changes in eye color. [17] developed a model capable of expressing 24 emotions solely through dynamic color changes, facing challenges due to reliance on average survey results and difficulty in distinguishing similar patterns. Tanaka et al. [21] addressed these issues by integrating blinking and varied speech patterns to convey different emotion intensities, consistently using the same colors for basic emotions to minimize confusion.

As previously discussed, there is a notable gap in research focusing on employing color to convey emotions in robots, particularly concerning dyads and the Vietnamese demographic.

3. Emotions and Dyads. Plutchik’s theory [18] likens emotions to colors, suggesting a correlation between them. He identified eight primary emotions, each corresponding to a primary color, and arranged them in a circular manner, akin to a color wheel. These emotions, in sequence, are joy, acceptance (later renamed trust), fear, surprise, sadness, disgust, anger, and anticipation. Emotions adjacent to each other on the circle are considered similar, while those opposite each other are viewed as opposites, resembling a hue ring. Each basic emotion is characterized by three levels of intensity, resulting in a total of 24 extended emotions. These eight basic emotions and their corresponding 24 extended variations, distinguished by varying intensity levels, are outlined in Table 3. It is important to note that our focus in this paper is specifically on exploring color-based expression models for these 24 extended emotions.

TABLE 1. Patterns of anger and anticipation extracted from Table 3

Emotion	Red	Green	Blue	Period
Fear	150	255	100	1800
Surprise	0	230	255	625

Dyads are combinations of two basic emotions, with primary dyads formed by pairing adjacent emotions on the circle. Secondary dyads arise from mixing emotions separated by one other emotion, while tertiary dyads result from combining emotions two steps apart. Table 2 lists these dyads across the three different levels. It is worth noting that the combination of surprise and disgust remains undefined in Plutchik’s framework.

Plutchik observed that it is more difficult to conceptualize mixtures of emotions that are further apart on the emotion circle compared to those that are closer. Consequently,

TABLE 2. List of three level of dyads [18]. “Acceptance” can be referred to as “Trust”.

Primary dyads	Secondary dyads
joy + acceptance = love	joy + fear = guilt
acceptance + fear = submission	acceptance + surprise = curiosity
fear + surprise = awe	fear + sadness = despair
surprise + sadness = disappointment	surprise + disgust = ?
sadness + disgust = remorse	sadness + anger = envy
disgust + anger = contempt	disgust + anticipation = cynicism
anger + anticipation = aggressiveness	anger + joy = prise
anticipation + joy = optimism	anticipation + acceptance = fatalism
Tertiary dyads	
joy + surprise = delight	
acceptance + sadness = resignation	
fear + disgust = shame	
surprise + anger = resentment	
sadness + anticipation = pessimism	
disgust + joy = morbidity	
anger + acceptance = dominance	
anticipation + fear = anxiety	

secondary and tertiary dyads may be less precise than primary dyads. Hence, we primarily focus on primary dyads at the moment. Based on Table 2, primary dyads include aggressiveness, optimism, love, submission, awe, disappointment, remorse, and contempt.

4. The Models of Emotions.

4.1. **The robot.** Figure 1 shows the design of the robot that is used in the experiments.



FIGURE 1. Design of our robot

The connection between microcomputers and PCs relies on serial communication, facilitating data exchange between the two. Users interact with the system via a Graphical User Interface (GUI) on the PC, offering various patterns to select from. Users are prompted to choose either Experiment 1 or Experiment 2. In both experiments, users express their extended emotions and dyads by pressing corresponding buttons on the interface. Each

extended emotion and dyad is preassigned a specific value (detailed in Section 4.2), which is then transmitted to the microcomputer. Upon receiving these values, the microcomputer triggers predefined parameters associated with each extended emotion or dyad. In Experiment 1, the microcomputer interprets the received values and activates LEDs to illuminate based on the selected emotions. For example, if a user selects “Annoyance”, the LED corresponding to “Anger” lights up and blinks at the lowest speed level of a basic emotion (see Figure 2). In Experiment 2, the microcomputer orchestrates a more dynamic response. Instead of simply illuminating, the LEDs gradually transition between colors based on the chosen dyads. For instance, if the user selects “Joy” and “Trust”, the LEDs may slowly shift between colors for “Joy” and “Trust” to create a sense of “Love” (see Figure 3). In summary, the interaction between the GUI on the PC, the microcomputer, and the LEDs enables users to explore and experience the relationship between emotions and visual feedback in two distinct experiments.

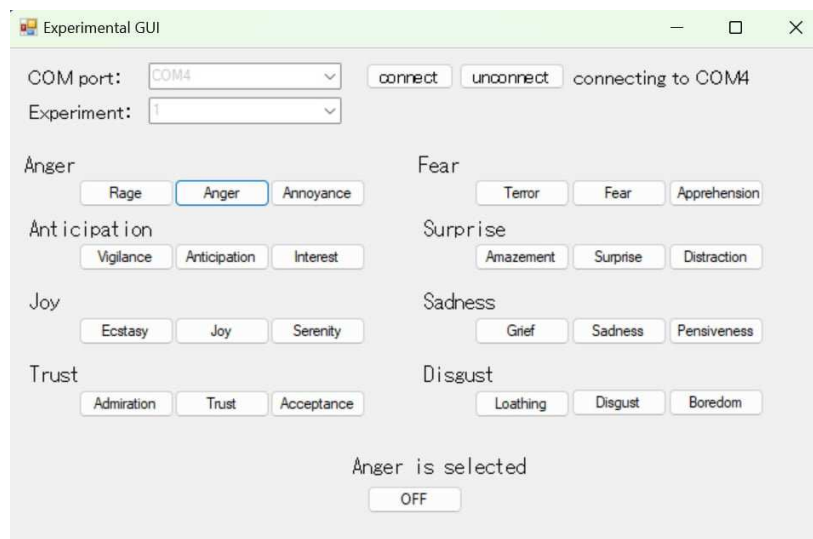


FIGURE 2. GUI for color control for Experiment 1

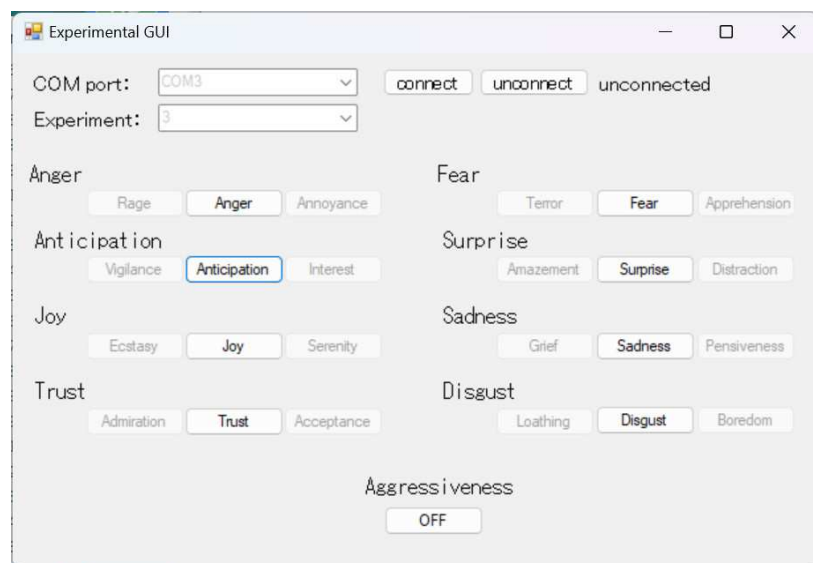


FIGURE 3. GUI for color control for Experiment 2

4.2. Model of emotions. Following the approach outlined by [21], Table 3 summarizes the emotions model utilized in this paper. The color names in the table adhere to the Munsell color system, while the color parameters (R, G, B) represent the PWM control values assigned to the common cathode LEDs.

TABLE 3. The model of 24 primary emotions

Basic emotion	Emotion	Color (R, G, B)	Color name	Period [ms]
Anger	Rage			300
	Anger	(0, 255, 255)	R (Red)	550
	Annoyance			800
Anticipation	Vigilance			900
	Anticipation	(50, 220, 255)	YR (Yellow Red)	1300
	Interest			1700
Joy	Ecstasy			750
	Joy	(0, 150, 255)	Y (Yellow)	1100
	Serenity			1450
Trust	Admiration			1500
	Trust	(150, 0, 255)	G (Green)	2100
	Acceptance			2700
Fear	Terror			1200
	Fear	(150, 255, 100)	PB (Purple Blue)	1800
	Apprehension			2400
Surprise	Amazement			500
	Surprise	(0, 230, 255)	YR (Yellow Red)	625
	Distraction			750
Sadness	Grief			2500
	Sadness	(255, 255, 0)	B (Blue)	3500
	Pensiveness			4000
Disgust	Loathing			1400
	Disgust	(50, 255, 150)	RP (Red Purple)	2450
	Boredom			3500

4.2.1. Model for extended emotion expressing using color blinking. This model is structured to express extended emotions through designated colors and varying blinking rates. The color references provided in Table 3 adhere to the Munsell color system, while RGB values are utilized to configure the PWM control parameters for the LEDs. With the control mechanism utilizing PNP-type transistors, a value of 255 (5 [V]) turns off the LEDs, whereas a value of 0 (0 [V]) results in the brightest light emission. The construction guidelines for this model include

- Assigning identical colors to emotions within the same fundamental category;
- Employing faster blinking rates for more intense emotions within each fundamental emotion category;
- Ensuring that all emotions are visually distinguishable from one another.

4.2.2. Model for dyads expressing using color gradient. In addition to employing solid colors, this model incorporates color gradient transitions between two basic emotions forming a dyad, representing the 8 primary dyads. Initially, the robot displays the two RGB colors corresponding to the combination of the two primary emotions outlined in

Table 3. Subsequently, the model continuously adjusts these colors in a subtle manner, generating a gradient effect.

In technical terms, dyads are depicted by blending two emotions through a gradient transition between two colors. The transition in RGB values from the first color to the second mimics a sinusoidal waveform. Specifically, the calculation for the RED component is as follows:

$$\text{RED} = \frac{\text{RED1} - \text{RED2}}{2} \sin\left(\frac{\pi i}{180}\right) + \left(\text{RED1} - \frac{\text{RED1} - \text{RED2}}{2}\right), \quad (1)$$

where RED1 represents the red value of the first color, and RED2 is the red value of the second color. The variable “ i ” ranges from 0 to 360. To depict the transition period, a delay, denoted as WAIT [ms], is introduced before moving to the next value of “ i ”. WAIT is determined by

$$\text{WAIT} = \frac{\text{PERIOD1} - \text{PERIOD2}}{360}, \quad (2)$$

where PERIOD1 and PERIOD2 correspond to the periods of the first and second color patterns, respectively.

For instance, to illustrate the emotion of awe, which is derived from the combination of fear and surprise, the corresponding pattern is detailed in Table 1.

5. Experimental Setup. Two experiments are designed to evaluate the efficiency of color-based models for expressing emotions and dyads among Vietnamese individuals. Here is a summary of each.

- Experiment 1: This experiment examines the effectiveness of a model that solely relies on colors to represent extended emotions.
- Experiment 2: This experiment assesses the effectiveness of a model that utilizes color gradients to express dyads.

5.1. Participants. Participants for both experiments were selected based on specific criteria to ensure relevance to the study’s focus on the Vietnamese cultural context. The participant pool consisted of Vietnamese individuals aged between 18 and 24, with a gender distribution of 70% male and 30% female, and all participants had no known visual impairments. This age range was chosen because younger individuals are more likely to be familiar with digital communication methods, making them well-suited to interpret emotional cues presented through visual media, such as color gradients. The participant pool consisted of both male and female individuals, ensuring gender diversity, although it remains a relatively homogeneous sample in terms of nationality. These experiments are conducted remotely through an online survey platform to ensure accessibility and convenience for the participants, who are expected to be proficient in computer usage. All experiments were conducted in a controlled environment to minimize external influences on participants’ ability to perceive and interpret the emotional cues presented through color gradients. Participants were asked to perform the tasks in a quiet room with neutral lighting, ensuring that their focus remained on the visual stimuli. Although the controlled setting helped in maintaining consistency across trials, it is important to note that real-world environments, where lighting and distractions vary, may influence how effectively participants interpret these emotional cues. To minimize biases from prior knowledge or assumptions, separate sets of participants are used for each experiment. In total, 170 participants take part across both experiments. They are presented with video recordings of robots displaying various emotion and dyad model scenarios and are then asked to respond to the provided questions.

5.2. Experiment design. In the two aforementioned experiments, we examined the efficacy of utilizing color, blinking, and gradients as means for robots to convey emotions, specifically focusing on Vietnamese cultural perceptions. Each extended emotion was linked with a specific color and blinking rate, and participants were tasked with identifying the emotions conveyed by the blinking colors exhibited by the robot. This approach aimed to assess the inherent association between particular colors and emotional states among Vietnamese participants. In Experiment 1, three extended emotions derived from a single basic emotion were simultaneously presented, utilizing color-blinking videos. Participants were provided with information about the basic emotions (e.g., Anger, Joy, and Fear) but not the specifics of the extended emotions. They were then required to determine which video corresponded to which extended emotions. For instance, within the “Anger” group, they might need to discern, “Video 1 represents Anger, Video 2 represents Annoyance, and Video 3 represents Rage”. There were a total of 8 questions, corresponding to 8 groups of extended emotions.

In Experiment 2, we utilized color gradients to represent the eight primary dyads. For example, to represent “Love”, we use transition between yellow for “Joy” and green for “Acceptance”, as shown in Figure 4. Participants evaluated each pattern based on the eight primary dyads using a five-point scale (5. Very-suited, 4. Suited, 3. Not-sure, 2. Not-very-suited, 1. Not-suited). Subsequently, the next pattern was displayed in a randomized order. The experiment concluded after all eight patterns had been presented. Participants rated their perception of the displayed emotion across eight distinct dyad categories on a scale from 0 to 5. For instance, when presented with the color yellow and green transitioning, typically associated with love, a participant might assign ratings such as 4 for “Love”, 2 for “Awe”, and 1 for “Remorse”.

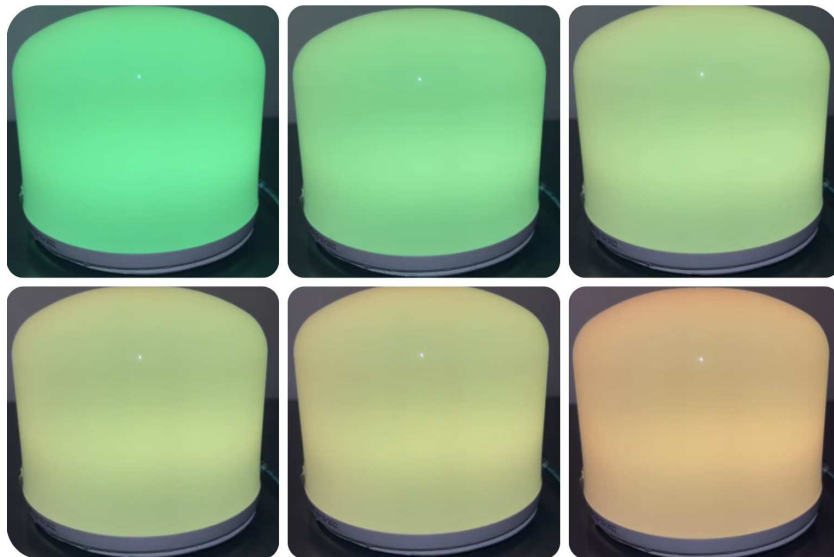


FIGURE 4. (color online) Representation of “Love” dyad

6. Experimental Results. All the experimental results are calculated as the ratio of participants who selected a specific evaluation emotion/dyad out of the total number of participants for a given studied emotion/dyad. This ratio provides insight into how closely the participants’ interpretations of the dyads align with the intended emotional expressions. By analyzing these ratios, we can assess the effectiveness of the color gradients used to represent various dyads and identify any potential areas of confusion or misinterpretation in the model.

6.1. **Experiment 1.** The results of Experiment 1 are succinctly illustrated in Figures 5 and 6. Figure 5 shows emotion groups that the model fails to represent. Figure 6 summarizes emotion groups that the model represents well. These heatmaps show the average ratings given by 80 participants for each emotion. The y -axis indicates the intended emotion (studied emotions), while the x -axis represents the participants' interpretations (evaluation emotions). The survey results presented in the figure suggest a clear pattern in the participants' ability to accurately identify moderate emotional expressions, while more pronounced difficulty is evident in distinguishing between nuanced variations of extended emotions conveyed by a robotic interface. Specifically, in Figure 5, the normal blinking speeds generally garnered higher correct identification rates, with 81% for “Anger”, 76% for “Joy”, and 70% for “Trust”, indicating a robust association between these moderate emotional states and their respective visual representations.

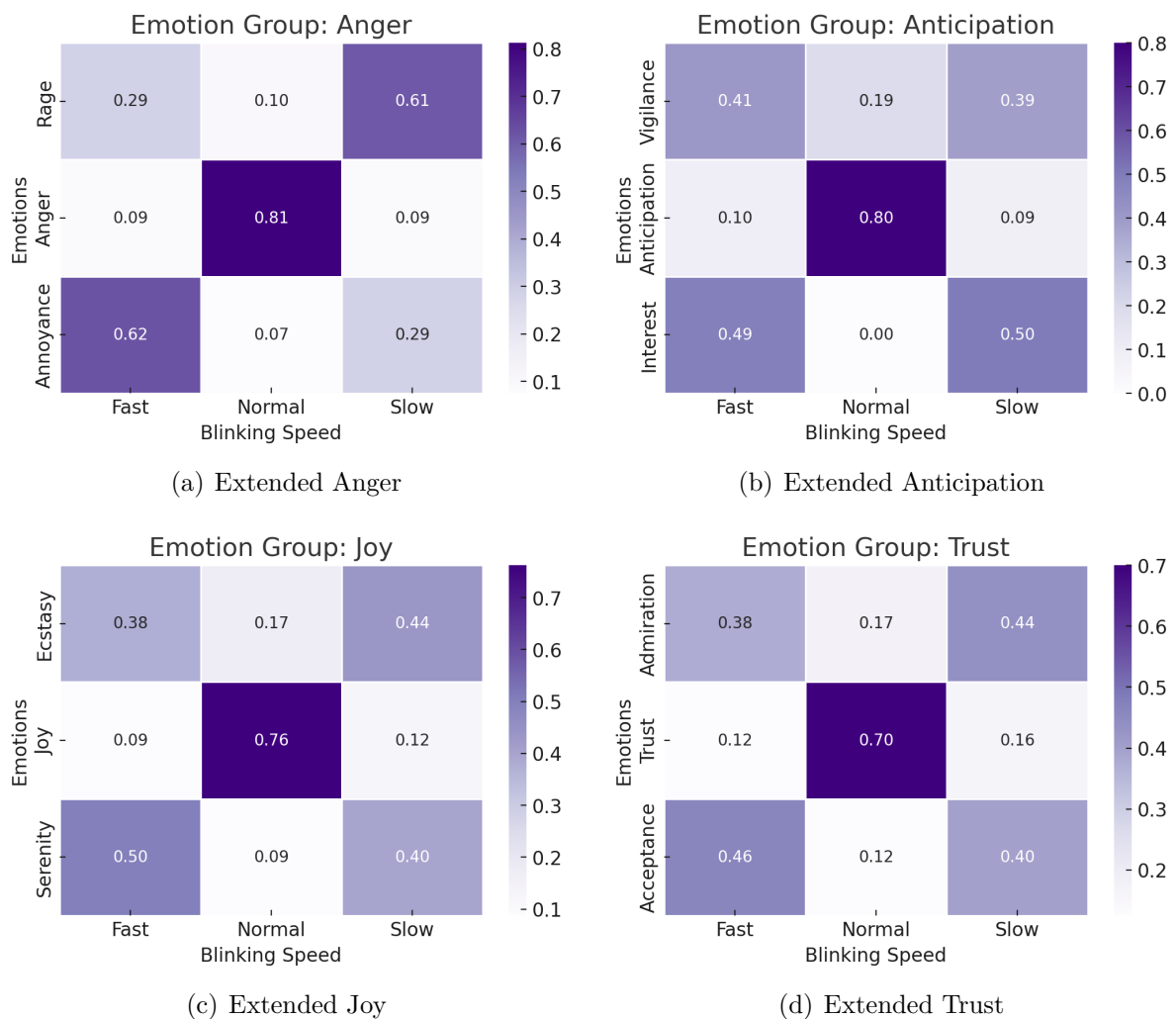


FIGURE 5. Emotion groups that the model fails to represent

However, the interpretation of extended emotions at varied blinking speeds reveals significant discrepancies. For instance, within the “Anger” emotion group, while the normal blinking speed accurately conveyed “Anger”, the fast blinking intended to depict “Rage” was predominantly misinterpreted as “Annoyance” by 62% of participants. This could indicate either an ineffectiveness of fast blinking to signify increased emotional intensity or a cultural-specific perception of blinking patterns.

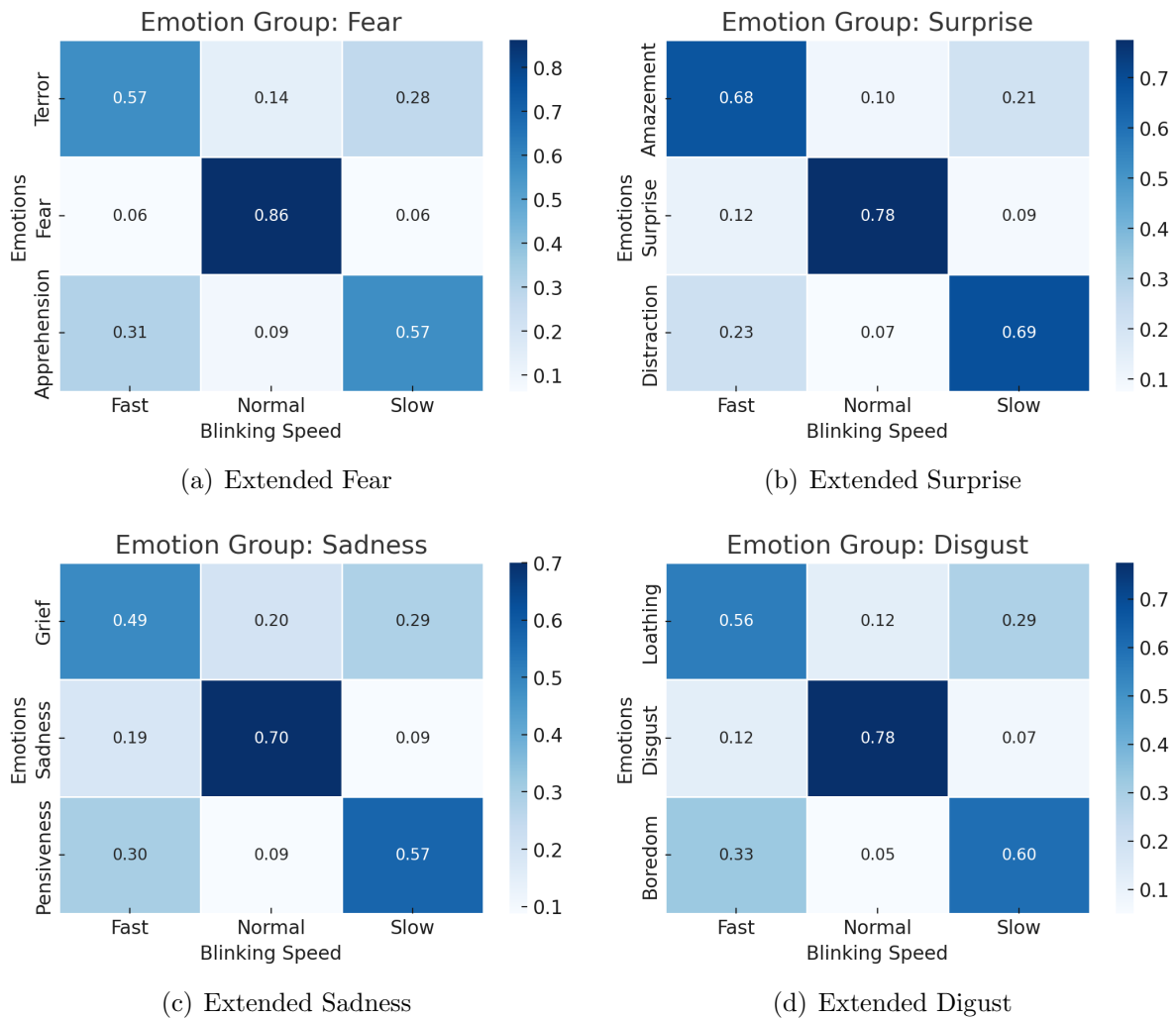


FIGURE 6. Emotion groups that the model represents well

Similarly, in the “Joy” group, while “Joy” itself at a normal blinking speed was accurately identified (76%), the fast blinking intended to express “Ecstasy” was interpreted as such by only 38% of participants. The slow blinking rate intended for “Serenity” showed a moderate identification rate of 50%, suggesting a partial but not complete alignment with participant perceptions.

The “Trust” group also displayed a moderate degree of accuracy, with “Trust” itself at a normal rate achieving a 70% correct identification rate. However, the variations such as “Admiration” at fast blinking and “Acceptance” at slow blinking were less accurately perceived, with 38% and 40% correct identification, respectively.

These findings illustrate that while moderate emotions are relatively well-understood and accurately linked to their visual cues, extended emotions, particularly at varied blinking speeds, tend to be misunderstood or misclassified. This could point towards the necessity for more refined or culturally specific calibration of visual cues in robotic systems to enhance the conveyance of a broader spectrum of emotions, particularly for those at higher or lower intensities than the moderate baseline.

The results in Figure 6 highlight a more successful alignment between participant perceptions and the intended emotional expressions conveyed through color and blinking speeds in robotic interfaces, particularly within the groups of Fear, Sadness, Surprise, and Disgust.

In the “Fear” emotion group, the participants accurately identified “Fear” at a normal blinking rate with a high correctness score of 86%, and “Terror” at a fast blinking rate achieved a moderate success rate of 57%. Interestingly, the slower blinking, intended to represent “Apprehension”, saw a significant correct identification rate of 57%, suggesting that slower blinking speeds may effectively convey a sustained state of fear.

The “Sadness” group also showed strong results, especially for “Sadness” at a normal blinking rate, which achieved a 70% accuracy. This suggests that participants could reliably discern a moderate, reflective state of sadness. “Grief”, depicted with fast blinking, was recognized correctly by 49% of the participants, while the slow blinking associated with “Pensiveness” again showed a notable correctness of 57%.

In the “Surprise” group, the normal blinking rate accurately conveyed “Surprise” itself with a high correctness score of 78%, demonstrating effective communication of sudden emotional shifts. Slow blinking, meant to represent “Distraction”, was also well-recognized, with a correctness rate of 69%.

Lastly, the “Disgust” group showed distinct effectiveness in conveying “Disgust” at a normal blinking rate, with a correct identification rate of 78%. This suggests a strong participant alignment with the visual cues intended to represent a clear aversive reaction. The slow blinking rate for “Boredom” was also significantly recognized with an accuracy of 60%.

These results suggest that the model employed for these emotion groups effectively utilized the blinking rates and associated colors to convey both intense and moderate emotional states. This alignment between robotic expressions and human perception underscores the potential for robotic systems to communicate complex emotional states effectively, particularly when the cues are appropriately matched with culturally and contextually understood signals.

6.2. Experiment 2. Experimental results for Experiment 2 is summarized in Figure 7. These heatmaps show the average score given by 90 participants for each dyad. The y -axis indicates the intended dyads (studied dyads), while the x -axis represents the participants’ interpretations (evaluation dyads). Figure 7 provides a comprehensive visualization of how participants in Experiment 2 perceived various emotional dyads through color gradients, indicating a wide range of interpretations and alignment with intended emotional expressions. Each cell in the heatmap represents the average score assigned by participants to a given color gradient with respect to its intended emotional dyad, revealing insightful patterns about the subjective perception of emotions conveyed through visual stimuli.

Among the successful conveyances, “Aggressiveness” was recognized with a high degree of accuracy, receiving an average rating of 1.97, which illustrates effective communication through the employed visual cues. Similarly, the strong alignment of 1.80 suggests that the color gradient used for “Love” was well-selected, resonating clearly with the participants and confirming the gradient’s suitability for conveying positive emotions. “Submission” and “Optimism” also received high ratings of agreement among participants, with scores of 1.12 and 1.14, respectively.

However, it is also important to observe how “Love” and “Optimism” were perceived in relation to each other. The score for interpreting “Love” as “Optimism” is 1.81, and vice versa it is 0.92. This overlap suggests that the visual cues used to represent “Love” and “Optimism” may carry a positive emotional valence that overlaps. This result could indicate either a successful broad appeal of the color gradient used, resonating with general positive emotions, or it might highlight a need to differentiate more clearly between these specific emotional states to avoid conflating distinct but related feelings.

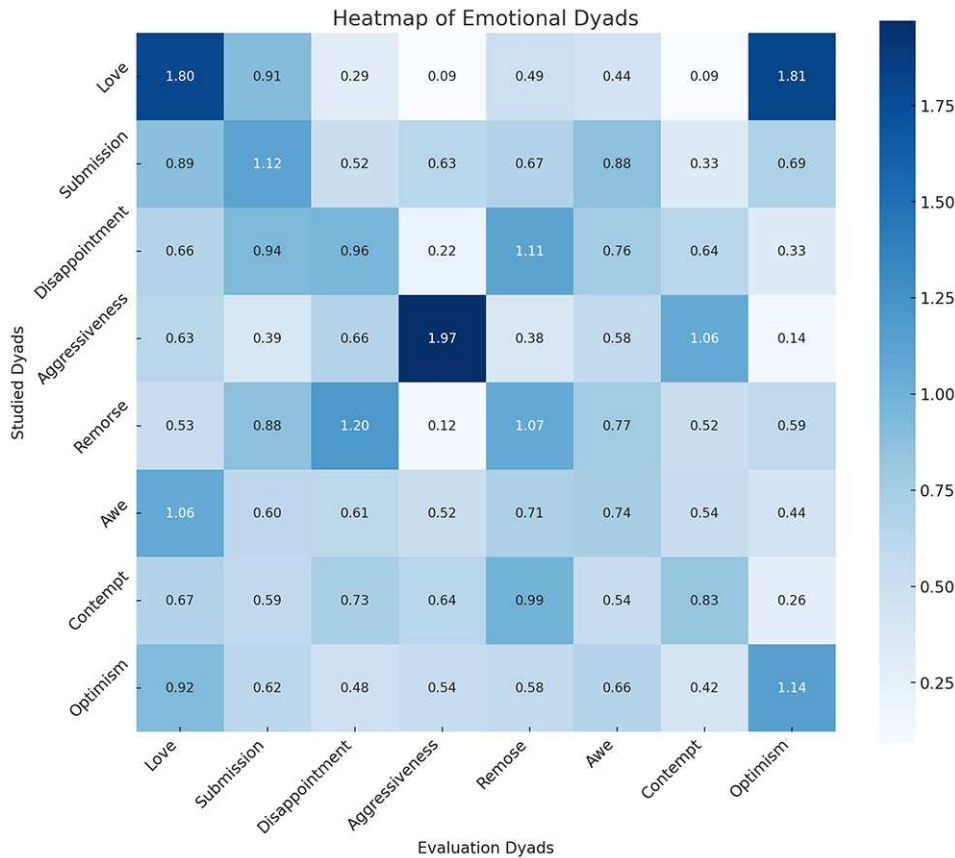


FIGURE 7. The result of Experiment 2

Significant misalignments were also evident, highlighting challenges in the methodological approach. For instance, “Disappointment” (as studied) and “Remorse” (as evaluated) received an average score of 1.11 and the opposite direction received the rate of 1.20, indicating substantial confusion among the participants. This score, one of the highest among non-diagonal entries, suggests that the visual representation intended for “Disappointment” was strongly misperceived as “Remorse”. This result calls into question the distinctiveness of the color gradients used, emphasizing the need for more differentiated color schemes to prevent the overlap of emotional signals.

Additionally, other dyads, such as “Remorse” and “Disappointment”, saw moderate to low scores even when correctly aligned, receiving scores of 1.07 and 0.96, respectively. These results indicate that, while certain emotions like “Aggressiveness” can be effectively conveyed, others require a more nuanced approach to enhance their perceptual distinctness and emotional clarity. The overall analysis of the heatmap demonstrates that while some emotional dyads are successfully communicated through color gradients, others are prone to misinterpretation or insufficient clarity. This variance underscores the complexity of using visual cues for emotional conveyance and points to the necessity for ongoing refinement in the selection and combination of colors to better match the intended emotional outputs. The insights from this experiment are crucial for improving visual communication strategies in areas ranging from marketing to interface design, where accurate emotional expression is key.

The ANOVA test results for this experiment are presented in Table 4. The results from a one-way Analysis of Variance (ANOVA) are performed in Experiment 2, detailing the statistical significance of differences in participants’ ratings across various emotional

TABLE 4. Results of one-way analysis of variance (ANOVA) for Experiment 2

Dyads	P-values	Dyads	P-values
Love	1.13×10^{-20}	Submission	2.61×10^{-11}
Awe	1.76×10^{-8}	Disappointment	1.97×10^{-4}
Remorse	3.22×10^{-10}	Contempt	4.46×10^{-5}
Aggressiveness	1.29×10^{-4}	Optimism	1.54×10^{-17}

dyads. The P-values listed reflect the likelihood that the observed differences in ratings for each dyad occurred by chance. The results show extremely low P-values for all the emotional dyads tested, indicating highly significant differences in how participants rated the color gradients intended to represent these emotions. For instance, the dyad “Love” shows a P-value of 1.13×10^{-20} , suggesting a statistically significant variance in the perception of this emotion across different presentations or conditions. This could imply that participants responded to “Love” with varying levels of agreement or disagreement about the effectiveness of its color gradient representation.

Similarly, “Optimism” demonstrates a strikingly significant variance with a P-value of 1.54×10^{-17} , underscoring that the visual representation of optimism was perceived differently across different trials or by different participants. This significant variance could be due to variations in the color gradient’s ability to consistently convey optimism, or it might reflect a broader range of interpretations among participants about what color best represents this emotion.

Other dyads like “Awe” and “Remorse” also showed significant differences in participant ratings, with P-values of 1.76×10^{-8} and 3.22×10^{-10} , respectively. These values affirm that the visual cues intended to represent these emotions led to varied perceptions, which could be influenced by personal experiences, cultural differences, or the subtlety and complexity of the emotions themselves.

The ANOVA results for “Aggressiveness” and “Disappointment” with P-values of 1.29×10^{-4} and 1.97×10^{-4} , respectively, although slightly higher than others, still indicate significant differences in perception. These findings highlight the challenges in creating universally understood visual representations of such complex emotions.

Overall, the consistently low P-values across all tested dyads in Table 4 strongly suggest that the color gradients used in the experiment significantly impacted participants’ emotional perceptions, indicating effective but varied conveyance of each intended emotional dyad. These results provide a robust statistical foundation to further explore and refine how colors can be optimized to communicate specific emotions more clearly and effectively.

7. Discussion.

7.1. Discussion on experimental results. This paper explored the potential of using color-based models for the expression of emotional dyads in robots, particularly within the Vietnamese cultural context, utilizing two distinct experimental setups. Experiment 1 focused on color and blinking patterns to express extended emotions from a single basic emotion. Results indicated that while moderate emotional states such as “Anger” “Joy” and “Trust” were generally well recognized, especially at normal blinking speeds, the nuances of more intense or subtle emotional states often eluded clear identification. This points to an inherent challenge in using simple visual cues like blinking speeds combined with color to effectively convey the full spectrum of human emotions, suggesting that adjustments or more intricate visual strategies may be required.

Experiment 2, which utilized color gradients to express primary dyads, further emphasized the complexity of emotional representation through color. While certain dyads like “Love” and “Optimism” were successfully communicated, receiving high recognition scores, others like “Disappointment”, which was often misinterpreted as “Aggressiveness”, demonstrated significant misalignments. These misinterpretations may be attributed to overlapping visual or emotional cues that the color gradients inadvertently presented, highlighting the nuanced influence of cultural perception on color interpretation. While color gradients are effective for representing simple emotions, expressing dyads presents unique challenges. The transition between two distinct colors can create visual ambiguity, as the blended hues may fail to clearly convey the intended emotional mix. Additionally, the emotional intensity of each individual color may be diluted in the gradient, making it more difficult for participants to identify both emotions equally. For example, the gradient representing “Contempt” (a combination of “Disgust” and “Anger”) might result in a color that lacks the distinctiveness of either emotion, leading to interpretation challenges. These findings underscore the difficulty in using simple gradients to communicate more complex emotional states and the importance of accounting for cultural variations in color perception.

7.2. Cultural adaptability. The mixed results from both experiments underscore the variability in emotional perception mediated by color, reflecting the intricate interplay between cultural context and emotional communication. These outcomes emphasize the necessity for a more refined approach in the deployment of color in robotic emotion expression systems, particularly when addressing a culturally diverse audience such as in Vietnam. The considerable variance in how different emotions and dyads were perceived, as highlighted by the ANOVA results, suggests that future models need to consider not only the emotional but also the cultural dimensions of color perception.

While this study focuses on the Vietnamese cultural context, it is important to consider how the proposed color-based emotional expression model could be adapted to other cultures. Cultural differences in color interpretation can significantly impact emotional communication. For example, the color white, which signifies mourning and death in Vietnamese culture, represents purity and peace in Western cultures. Similarly, colors like yellow may carry different emotional connotations across cultures (e.g., Joy in Western societies but Jealousy in others).

To ensure the broader applicability of the model, future research should explore how these color gradients and emotional associations are perceived in other cultural contexts. Studies such as those by [23] have shown that cultural variations in non-verbal cues can alter emotional interpretations in human-robot interactions. It would be beneficial to extend this research by conducting cross-cultural experiments to evaluate whether the dyads and primary emotions expressed through color gradients retain their intended meaning in diverse environments. The potential adaptability of the model will be tested by exposing participants from various cultural backgrounds to the same color gradients and comparing their emotional interpretations.

8. Future Work. Future research should aim to deepen our understanding of the cultural implications of color in emotional expression and refine color-based models to improve their specificity and cross-cultural applicability. It is critical to expand these studies to include a wider range of emotional states and test these models in diverse cultural settings. Such research will be essential for advancing the field of robotic emotional communication and ensuring that the models are adaptable across different cultural contexts. For instance, exploring how color interpretations vary across regions and adjusting the model

accordingly could significantly enhance the robot’s ability to communicate emotions universally. In particular, we plan to investigate how different regions of Vietnam (North, Central, and South) interpret colors, and how these regional variations in color perception may influence emotional expression. By refining the color system based on these findings, we aim to develop a culturally-specific color model for Vietnamese users, potentially creating a new framework for robotic emotional communication.

In addition to focusing on color, future research should investigate the use of vocal bursts – non-verbal sounds such as sighs, laughter, or gasps – combined with color gradients for a multimodal emotional expression system. This combined approach would allow for a more nuanced representation of complex emotions, such as dyads. For example, while a gradient transition from yellow (Joy) to green (Trust) may visually convey “Love” pairing it with a soft, soothing vocal burst could enhance emotional clarity and reduce ambiguity. Similarly, a color gradient representing “Contempt” (“Disgust” and “Anger”) could be paired with a sharper, more intense vocal burst to emphasize the conflicting emotional states. This multimodal combination of visual and auditory cues could significantly improve the accuracy and depth of emotional communication in robots.

Moreover, expanding the participant pool to encompass individuals from various age groups, educational backgrounds, and cultural contexts will be crucial for assessing the generalizability of the findings beyond the Vietnamese demographic. Testing the model with participants from a variety of cultural backgrounds will provide valuable insights into how well the combined color and vocal burst system communicates emotions across different regions. We will also compare cross-cultural differences in emotion interpretation, ensuring that our models can adapt to diverse settings, both within Vietnam and internationally.

It will also be important to investigate the influence of the experimental environment on the results, as varying environmental factors may impact participants’ interpretations. Factors such as lighting, background noise, or the presence of distractions could alter how participants perceive and interpret both visual and auditory cues. Ensuring that the model is robust enough to function effectively in dynamic, real-world environments will be a key challenge for future studies.

Finally, a broader exploration of how these multimodal systems are interpreted across cultures will be essential to determine whether the integration of vocal bursts enhances or complicates emotional interpretation in different regions. By incorporating both visual and auditory elements into the emotional communication model, researchers can significantly enhance the emotional expressiveness of robots, making them more relatable and capable of nuanced interactions in diverse cultural settings. Additionally, the future development of a Vietnamese-specific color system will allow for more precise emotional communication, enhancing the robot’s ability to engage with users across various cultural backgrounds, starting with a deeper understanding of regional color perception within Vietnam.

9. Conclusion. In this paper, the exploration of color-based models for expressing emotions and dyads in robots has demonstrated both the potential and limitations of this approach within a Vietnamese cultural context. The paper confirmed that while certain emotional expressions, particularly those associated with positive emotions, can be effectively communicated through color gradients, more work is needed to refine the representation of complex emotional dyads and culturally nuanced expressions.

This research paves the way for the next generation of culturally competent robotic companions that can engage in more meaningful and emotionally resonant interactions

with users from diverse backgrounds, ultimately enhancing the integration of robots into daily life and mental health support frameworks.

REFERENCES

- [1] T. Suzuki, S. Yamada, T. Nomura and T. Kanda, Do people prefer robots over humans as daily communication partners?: Relationship to social anxiety in conjunction with the appearance of the robots, *Journal of Japan Society for Fuzzy Theory and Intelligent Information*, vol.31, no.5, pp.789-796, 2019.
- [2] T. Suzuki, S. Yamada, T. Nomura and T. Kanda, Social anxiety and human-robot interaction, *Journal of the Society of Instrument and Control Engineers*, vol.61, no.3, pp.214-217, 2022.
- [3] Y. Bakhtiar, W. Jinseok, T. Takeda and J. B. N. Kubota, Robot partners based on empathy for elderly care, *The 31st Fuzzy System Symposium Conference*, pp.25-28, 2014.
- [4] Y. Bakhtiar, W. Jinseok, T. Takeda, J. B. Kubota and N. Naoyuki, The life support system for the aged uses the pet robot as an interface – The development of the core system, *Proc. of IIAE Annual Conference*, pp.34-36, 2016.
- [5] C. Breazeal, Function meets style: Insights from emotion theory applied to HRI, *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol.34, no.2, pp.187-194, 2004.
- [6] N. Rawal and R. M. Stock-Homburg, Facial emotion expressions in human-robot interaction: A survey, *International Journal of Social Robotics*, vol.14, no.7, pp.1583-1604, 2022.
- [7] Z. Liu, M. Wu, W. Cao, L. Chen, J. Xu, R. Zhang, M. Zhou and J. Mao, A facial expression emotion recognition based human-robot interaction system, *IEEE CAA J. Autom. Sinica*, vol.4, no.4, pp.668-676, 2017.
- [8] M. Spezialetti, G. Placidi and S. Rossi, Emotion recognition for human-robot interaction: Recent advances and future perspectives, *Frontiers in Robotics and AI*, vol.7, 532279, 2020.
- [9] R. Nimmagadda, K. Arora and M. V. Martin, Emotion recognition models for companion robots, *The Journal of Supercomputing*, vol.78, no.11, pp.13710-13727, 2022.
- [10] P. Valdez and A. Mehrabian, Effects of color on emotions, *Journal of Experimental Psychology: General*, vol.123, no.4, 394, 1994.
- [11] L.-C. Ou, M. R. Luo, A. Woodcock and A. Wright, A study of colour emotion and colour preference. Part I: Colour emotions for single colours, *Color Research & Application*, vol.29, no.3, pp.232-240, 2004.
- [12] N. Kaya and H. H. Epps, Relationship between color and emotion: A study of college students, *College Student Journal*, vol.38, no.3, pp.396-405, 2004.
- [13] M. Hemphill, A note on adults' color-emotion associations, *The Journal of Genetic Psychology*, vol.157, no.3, pp.275-280, 1996.
- [14] S. Sugano and T. Ogata, Emergence of mind in robots for human interface – Research methodology and robot model, *Proceedings of IEEE International Conference on Robotics and Automation*, vol.2, pp.1191-1198, 1996.
- [15] M. Gotoh, M. Kanoh, S. Kato, T. Kunitachi and H. Itoh, Face generation using emotional regions for sensibility robot, *Transactions of the Japanese Society for Artificial Intelligence*, vol.21, no.1, pp.55-62, 2006.
- [16] H. Teshi, K. Terada and A. Ito, Effect of emotion expression with blinking coloured eyes of a robot on emotional story understanding, *Journal of Human Interface Society*, vol.17, no.4, pp.445-456, 2015.
- [17] K. Terada, A. Yamauchi and A. Ito, Artificial emotion expression for a robot by dynamic colour change, *2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication*, pp.314-321, 2012.
- [18] R. Plutchik, *Emotion: A Psychoevolutionary Synthesis*, Harper & Row, New York, 1980.
- [19] M. M. Aslam, Are you selling the right colour? A cross-cultural review of colour as a marketing cue, *Journal of Marketing Communications*, vol.12, no.1, pp.15-30, 2006.
- [20] T. J. Madden, K. Hewett and M. S. Roth, Managing images in different cultures: A cross-national study of color meanings and preferences, *Journal of International Marketing*, vol.8, no.4, pp.90-107, 2000.
- [21] S. Tanaka, N. T. Mai, K. Hashikura, M. A. S. Kamal, I. Murakami and K. Yamada, The model to express emotions for robots using colors and blinks, *International Journal of Innovative Computing, Information and Control*, vol.20, no.1, pp.61-73, 2024.

- [22] R. Plutchik, The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice, *American Scientist*, vol.89, no.4, pp.344-350, 2001.
- [23] J. Urakami and K. Seaborn, Nonverbal cues in human-robot interaction: A communication studies perspective, *ACM Transactions on Human-Robot Interaction*, vol.12, no.2, pp.1-21, 2023.

Author Biography



Dao Thanh Huyen received a Master's degree from the Posts and Telecommunications Institute of Technology in 2015. Currently, she is working as a lecturer at the Posts and Telecommunications Institute of Technology. Her research fields are control theory, networks and communication devices.



Nghia Thi Mai received the B.S., M.S. and Dr. Eng. degrees from Gunma University, Gunma, Japan in 2009, 2011 and 2014, respectively. From 2014 to 2015, she was with the Human Resources Cultivation Center, Gunma University, Gunma, Japan as a research associate. From 2015 to 2021, she worked on research on damping control for automobiles at Exedy Co., Ltd. Since 2022, she has been working as a lecturer at the Faculty of Electronics Engineering 1, Posts and Telecommunications Institute of Technology (PTIT). In addition, she is currently working as a visiting associate professor and part-time lecturer at the Department of Electronics and Mechanical Engineering, Gunma University. Her research interest includes Smith predictor, internal model control and robotics.



Suzuka Tanaka received the B.E. degree in Mechanical Science and Technology from Gunma University, Japan in 2023. Now, she is a master course student at Gunma University. Her research interests include intelligent robots.



Kotaro Hashikura received the B.S. degree in Mechanical Engineering from Kyushu Institute of Technology, Fukuoka, Japan, 2006; the M.S. degree of Informatics from Kyoto University, Kyoto, Japan; 2010, and the Doctor degree in Engineering from Tokyo Metropolitan University, Tokyo, Japan, 2014. From 2014 until 2018, he had been a Project Research Associate at the Faculty of System Design, Tokyo Metropolitan University. He is currently an assistant professor at Graduate School of Science and Technology, Gunma University, Japan. His research interests include time-delay-related control techniques, such as deadbeat, preview-prediction and repetitive controls. He is a member of IEEE, ISCIE and SICE.



Md Abdus Samad Kamal received the B.Sc. degree in Electrical and Electronic Engineering from Khulna University of Engineering and Technology (KUET), Khulna, Bangladesh in 1997; Master and Doctor degrees from Kyushu University from Graduate School of Information Science and Electrical Engineering, Japan in 2003 and 2006, respectively. He was a post-doctoral fellow in Kyushu University till November 2006. He is currently an associate professor at Graduate School of Science and Technology, Gunma University, Japan. His current research interests are reinforcement learning, intelligent transportation systems, and multiagent systems. He is a member of IEEE and SICE.



Iwanori Murakami received his Ph.D. Eng. from Gunma University in 1997. He is currently an associate professor at Gunma University. His research interests include robotics, applied electromagnetics and machines, and superconducting levitation applications.



Kou Yamada received B.S. and M.S. degrees in Electrical and Information Engineering from Yamagata University, Yamagata, Japan, 1987 and 1989, respectively; and the Dr. Eng. degree from Osaka University, Osaka, Japan in 1997.

He is currently a full-time professor at Graduate School of Science and Technology, Gunma University, Japan. His research interests include robust control, repetitive control, process control and control theory for inverse systems and infinite-dimensional systems. Prof. Yamada received the 2005 Yokoyama Award in Science and Technology, the 2005 Electrical Engineering/Electronics, Computer, Telecommunication, and Information Technology International Conference (ECTI-CON2005) Best Paper Award, the Japanese Ergonomics Society Encouragement Award for Academic Paper in 2007, the 2008 Electrical Engineering/Electronics, Computer, Telecommunication, and Information Technology International Conference (ECTI-CON2008) Best Paper Award and the 4th International Conference on Innovative Computing, Information and Control Best Paper Award in 2009, the 14th International Conference on Innovative Computing, Information and Control Best Paper Award in 2019, Outstanding Achievement Award from Kanto Branch of Japanese Society for Engineering Education in 2022, JSME (The Japan Society of Mechanical Engineers) Education Award in 2023 and the 2024 Electrical Engineering/Electronics, Computer, Telecommunication, and Information Technology International Conference (ECTI-CON2024) Best Paper Award. He is a member of IEEE and SICE, and a fellow of JSME.