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INVESTIGATING THE EFFECTIVENESS OF COLOR-BASED EMOTION MODELS FOR ROBOTS ACROSS VIETNAMESE AND JAPANESE CULTURES

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Abstract. *Robots today are increasingly expected to interact with humans in ways that feel natural and engaging, particularly in healthcare and social service environments. Effective emotional expression is a key factor in helping robots carry out these tasks successfully. Traditional methods for enabling robots to express emotions often involve complex designs, which can be both costly and impractical for large-scale implementation. In response, several studies have proposed a simpler, color-based approach to robot emotion expression, aiming to achieve effective results with minimal complexity. However, most of these studies have focused on specific cultural groups, overlooking potential variations in how different cultures interpret colors associated with emotions. This lack of cross-cultural consideration limits the generalizability of these models. Notably, no prior research has examined color-based emotion models across both Japanese and Vietnamese cultural settings, even though interpretations of color may vary significantly between these two cultures. This study is the first to explore the effectiveness of simple color-based emotion models specifically within Japanese and Vietnamese contexts. Through experimental testing, we evaluate how well these models convey nuanced emotional states without relying on traditional human-like expressions and whether the models adapt across cultural boundaries. Our findings reveal three main insights: 1) certain colors consistently evoke similar emotional responses among both Japanese and Vietnamese participants, supporting the partial effectiveness of color-based models; 2) some colors elicit different emotional interpretations between the two cultural groups, indicating cultural nuances in perception; and 3) the model demonstrates higher consistency and effectiveness in the Japanese context across different tasks. These insights highlight the need for further exploration into culturally tailored approaches. Our results emphasize the practicality of culturally sensitive, color-based emotion models as a scalable solution for enhancing robot communication, particularly in Japanese and Vietnamese healthcare settings. This work also lays the groundwork for broader applications in emotion-sensitive fields that require cross-cultural adaptability.*

Keywords: Robot, Emotion, LED, Color, Gradation, Cultural differences

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1. **Introduction.** In recent years, robot-human interactions have garnered significant attention from research communities due to the expanding role of robots in various domains. Robots are increasingly integrated into diverse aspects of daily life, from industrial automation to personal assistance and education. A notable surge in robot applications is evident in healthcare, where patients with social anxiety often find it more comfortable to engage with robots – particularly those with metallic appearances – rather than with human caregivers [1, 2, 3]. As demand for robots rises, research has further explored their potential in counseling settings [4] and the development of robotic companions designed to enhance mental well-being among the elderly. These robots are seen as promising alternatives to traditional human caregivers, addressing essential companionship and care needs [5, 6].

For robots to effectively interact with humans, serve as assistants, and even act as companions, they must go beyond task execution. They need to possess a user-friendly interface, communicate effectively with humans, and demonstrate emotional expressiveness [7, 8]. These qualities make robots appear more human-like, facilitating smoother and more natural interactions. Among these, one of the most crucial aspects in human-robot interaction is the robot's ability to convey emotions. Emotion expression is a significant step toward fostering interactions that feel more relatable and natural, ultimately enhancing the quality of human-robot communication. This advancement is expected to lead to more meaningful and effective interactions, bridging the gap between technological functionality and human social needs [9]. To tackle the challenges of emotional expression in robots, previous research has proposed various designs that incorporate human-like characteristics to create interfaces capable of conveying emotions [10]. These designs include mechanisms such as facial expressions [10], body language and gestures [11], speech prosody [12], and other multimodal approaches [9, 13, 14, 15].

However, designing and manufacturing robots with these advanced interfaces is a costly and time-consuming process. Studies indicate that while these systems effectively express emotions, they are resource-intensive and financially demanding, making them impractical for widespread use, particularly in fields like nursing and mental healthcare. Research by [16] demonstrates that facial emotion recognition systems in human-robot interaction (HRI) often require sophisticated processing capabilities and specialized sensors, which drive up both costs and maintenance needs. The complexity of these systems also increases their susceptibility to errors in uncontrolled environments, limiting their scalability. Similarly, [17] finds that deep learning models for real-time emotion recognition can achieve high accuracy in controlled settings, yet their performance significantly drops in dynamic, real-world conditions.

Therefore, there is a clear need for simpler robot interface designs that can effectively convey emotions while keeping costs low and maintaining ease of manufacturing, storage, and maintenance. Approaches like color-based emotional expressions offer a viable solution, as they eliminate the need for expensive hardware while still enabling robots to communicate a wide range of emotions. Research has shown that non-verbal cues like color are effective in conveying emotions and are much less resource-intensive [18, 19]. A substantial body of literature [20, 21, 22, 23, 24, 25] supports the concept that colors inherently carry emotional significance, making them an intuitive tool for robots to express feelings [9, 26, 27, 28, 29]. By incorporating color-based expressions, robots could serve as affordable, accessible companions for mental health support, offering an innovative means to assist patients in mental health care.

However, existing studies on color-based emotion expression models for robots have primarily focused on specific cultural settings, with little consideration for extending these models across diverse cultures to ensure generalizability. Cultural diversity significantly impacts color interpretation, as different societies attribute unique meanings to colors [24, 30, 31]. For example, [30] highlights how yellow signifies envy in Germanic cultures, purity and royalty in Chinese contexts, and happiness in Korean culture. Similarly, the color white holds varying cultural meanings; in Japan, it represents purity and is associated with weddings and traditional aesthetics, while in Vietnam, it is predominantly linked to mourning and death, symbolizing both purity and spirituality but carrying a strong association with mortality.

Specifically, the model of color studied in this work is built upon Plutchik's emotional theory, which defines eight primary emotions – joy, trust, fear, surprise, sadness, disgust, anger, and anticipation – and their corresponding color representations [32]. However, despite its broad theoretical foundation, Plutchik's model has primarily been studied in Western contexts, and its applicability across different cultural settings remains underexplored. For instance, red is commonly associated with anger in both Japanese and Vietnamese contexts, but it also conveys prosperity and good fortune in Vietnam, particularly in Lunar New Year celebrations, whereas in Japan, it is frequently used in warning signs and traditional festivities [31, 33]. Similarly, yellow, often linked to joy, symbolizes bravery and caution in Japan, yet in Vietnam, it is historically associated with royalty and prosperity, as seen in the yellow imperial robes worn by Vietnamese emperors [21]. Blue is widely connected to sadness and calmness in Japan, but in Vietnam, it lacks strong emotional connotations and is instead linked to stability and peace [20]. Purple-blue, which is used in our model to represent fear, is associated with mystery and spirituality in Japan, while in Vietnam, it is more commonly linked to mourning and nostalgia, particularly in poetry and traditional dress [21].

These cultural nuances are essential for effective emotional expression in robots, as colors can profoundly shape human perceptions and responses. In human-machine interactions, using colors inaccurately to express emotions could lead to misunderstandings, misinterpretations, and ineffective communication. For instance, employing white to convey positive emotions in Vietnamese culture might cause confusion due to its traditional association with mourning. Consequently, cultural sensitivity in color selection is crucial for ensuring robots can communicate emotions accurately and meaningfully across diverse cultural contexts. Such misunderstandings could not only reduce the effectiveness of a robot's emotional expressions but also weaken trust and engagement between humans and machines. These cultural distinctions highlight the importance of research focused on developing a color-based emotion model that can be adapted to multiple cultures, thereby enhancing robots' ability to communicate emotional states in a culturally appropriate manner. A number of studies have explored the capacity for multimodal emotional expression in cross-cultural contexts [15, 24, 25, 34, 35, 36, 37]. These works are rare but essential, as they investigate how different modes of emotional expression, such as gestures, facial cues, and vocal tones, can be perceived across diverse cultural backgrounds.

Building on prior research that investigated color-based emotion expression models for robots in Japanese contexts [38, 39], we aim to assess the effectiveness of these models across both Vietnamese and Japanese cultures. By replicating the experiment in Vietnam and conducting a detailed analysis of the results with previous works, our goal is to gain deeper insights into this approach to emotion expression, ultimately working toward a more adaptable, generalizable model that can account for complex cultural differences. In this study, we compare three emotion expression models within Vietnamese and Japanese settings:

1) a model using colors to convey eight basic emotions,
2) a model that incorporates color and blinking to indicate emotion intensity, and

3) a model using color gradients to express primary emotional dyads.

The results of this research indicate that while color-based emotion expression models have some cross-cultural applicability, cultural nuances play a significant role in how colors and visual cues, such as blinking rates, are interpreted. Specifically, certain colors were found to evoke similar emotional responses among Japanese and Vietnamese participants, suggesting that a foundational set of color-emotion associations may be understood universally. However, differences in perception of other colors and blinking rates highlight the need for cultural customization to avoid misinterpretations and enhance communication effectiveness. Additionally, the model demonstrated higher consistency and effectiveness in the Japanese context, which may suggest that certain design elements align more naturally with specific cultural frameworks.

The structure of this paper is organized as follows. Section 2 reviews prior research on color-based models for robots' emotional expression and explores studies on cultural differences. Section 3 defines the basic emotions, their extensions, and combinations as dyads relevant to this study. Section 4 provides an in-depth look at the models used for expressing emotions and emotional dyads through color. The methodology, including the experimental setup and procedures, is detailed in Section 5. Section 6 summarizes the findings from the experimental phase. Section 7 discusses these results, examining their implications and providing insights into their significance. Finally, Section 8 presents the concluding remarks, observations, and suggestions for future research directions in this field.

2. **Related Works.** Numerous approaches have been developed to associate colors with emotions, with Plutchik's model [32] being among the most influential. Plutchik demonstrated that colors could be linked to core emotions and, when combined, could convey more intricate emotional expressions. He initially identified eight primary emotions – joy, acceptance (later revised to trust [40]), fear, surprise, disgust, anger, and anticipation – and expanded these by introducing three intensity levels for each, yielding a total of 24 distinct emotional variations. Furthermore, Plutchik introduced the concept of dyads, combinations of two primary emotions, to represent more complex emotional experiences.

Numerous studies have investigated the use of colors to convey emotions in robots [26, 27, 28, 29, 39]. Sugano and Ogata [26] 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). [27] 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. [28] used a robot named Nao to depict eight basic emotions through changes in eye color. [29] 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. [39] 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.

Other research has explored expressing emotions in robots through multimodal approaches that combine color with other cues [15, 41, 42, 43, 44, 45, 46, 47]. For instance, Löffler et al. [15] systematically designed and validated 28 different uni- and multimodal expressions for the basic emotions – joy, sadness, fear, and anger – using color, motion, and sound. Their findings suggest that combining color with planar motion offers an effective means of conveying these emotions, with specific modalities being more effective for certain emotions: joy was best conveyed via color and motion, sadness via sound, fear via motion, and anger via color. Similarly, Fernández-Rodicio et al. [47] presented a method for modeling a robot's expressiveness by combining symbolic and emotional dimensions, where each can be generated independently. The study introduces an expressiveness architecture that uses predefined multimodal expressions – including color changes – to convey emotions such as happiness, anger, sadness, and fear. The research demonstrates that dynamic light patterns can effectively communicate emotions, underscoring the importance of color in robotic emotional expression. Furthermore, Feldmaier et al. [43] evaluated an RGB-LED-based emotion display for affective agents, focusing on how dynamic light patterns can convey emotions such as happiness, anger, sadness, and fear. Their study demonstrated that certain basic emotions could be recognized by human observers through specific color patterns, highlighting the potential of using color as a primary modality for emotion expression in robots. However, the cost and complexity of implementing multimodal emotion expression in robots remain key challenges. While combining color, motion, and sound enhances emotional communication, it also increases the hardware and computational requirements. For instance, integrating LED-based displays, motorized motion systems, and synchronized sound modules requires additional power consumption and precise calibration, which may not be feasible for low-cost or resource-limited robotic platforms.

There is a substantial body of work that investigates cross-cultural differences in robot-human interaction design [25, 34, 35, 36, 37] using different models. Specifically, many studies examine how varying cultural attitudes, social norms, and levels of technological acceptance shape user expectations and preferences in robot interaction. For instance, some cultures may emphasize politeness and indirect communication in interactions with robots, reflecting broader societal norms [48, 49]. Conversely, other cultures may prioritize efficiency and direct interaction styles, particularly in contexts where robots are used in task-oriented roles, such as elderly care or industrial assistance [35, 36]. These differences underline the importance of tailoring robot interaction designs to align with cultural values, thus enhancing acceptance and efficacy across diverse user groups [25].

However, most color-based methods are designed specifically for particular demographic contexts, such as English or Japanese-speaking users, without accounting for the cultural sensitivities that may vary across other demographics. This gap highlights a need for research focused on developing a generalized model that accommodates cultural nuances. In particular, there is limited exploration of interaction dyads and comparative studies involving Japanese and Vietnamese demographics. Addressing this gap could improve the cross-cultural applicability of color-based models in human-robot interaction design.

3. **Emotions & Dyads.** Plutchik's emotional theory [32] draws an analogy between emotions and colors, proposing a structured relationship between the two. He identified eight core emotions, each linked to a primary color, and organized them in a circular layout similar to a color wheel. These primary emotions – joy, acceptance (trust), fear, surprise, disgust, anger, and anticipation – are arranged so that adjacent emotions share similarities, while those positioned opposite each other reflect opposing qualities, mirroring a hue circle. Each core emotion is further divided into three intensity levels, producing 24 extended emotions in total. Table 3 illustrates these basic emotions and their 24 nuanced variations, each defined by a distinct intensity level.

It is important to note that our focus in this paper is specifically on exploring color-based expression models for 8 basic emotions and their intensity.

Dyads, as combinations of two fundamental emotions, provide a nuanced framework for understanding emotional complexity. Primary dyads are formed by pairing 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

TABLE 2. List of three level of dyads [32]. 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 = resignarion	
fear + disgust = shame	
surprise + anger = resentment	
sadness + anticipation = pessimism	
disgust + joy = morbidness	
anger + acceptance = dominance	
anticipation + fear = anxiety	

positioned next to each other on the circular model, highlighting close emotional relationships. In contrast, secondary dyads are constructed by merging emotions that have one intervening emotion between them, indicating a moderate level of emotional contrast. Tertiary dyads arise from combining emotions separated by two other emotions on the circle, reflecting the greatest level of contrast within the dyadic structure. Table 2 categorizes these dyads across the three structural 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, 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.

Serial communication serves as the foundational link between microcomputers and PCs, enabling seamless data transfer between the devices. Users engage with the system through a PC-based Graphical User Interface (GUI), which presents multiple selectable patterns. Within the GUI, users can choose from three experimental options: Experiment 1, Experiment 2, or Experiment 3. During each experiment, users indicate their emotions and dyads by selecting corresponding buttons on the interface. Each emotion and dyad is assigned a distinct value (as outlined in Section 4.2), which is then communicated to the

FIGURE 1. Design of our robot

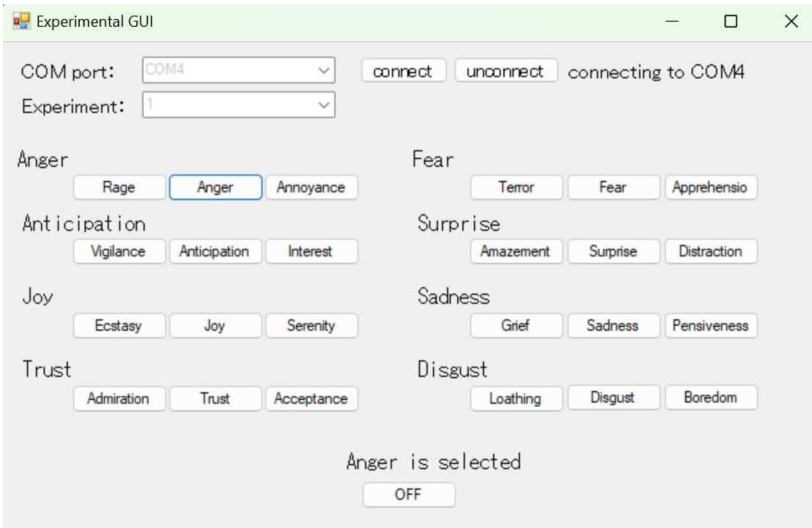

FIGURE 2. GUI for color control for Experiment 1

microcomputer. Upon receipt, the microcomputer activates predefined parameters tied to each emotion or dyad.

In Experiment 1, the microcomputer interprets the incoming values and activates LEDs corresponding to the selected emotions. For instance, if the user chooses 'Joy', the LED associated with 'Joy' illuminates (see Figure 2).

In Experiment 2, the microcomputer similarly interprets the received values but activates LEDs with added dynamics based on the selected emotions. For example, if 'Annoyance' is chosen, the LED linked to 'Anger' illuminates and blinks at the minimum speed designated for basic emotions (see Figure 2).

Experiment 3 involves a more complex response from the microcomputer. Instead of static lighting, LEDs gradually transition between colors in alignment with selected dyads. For example, if the user selects Joy and Trust, the LEDs slowly alternate between colors for Joy and Trust, evoking a blended sense of Love (see Figure 3).

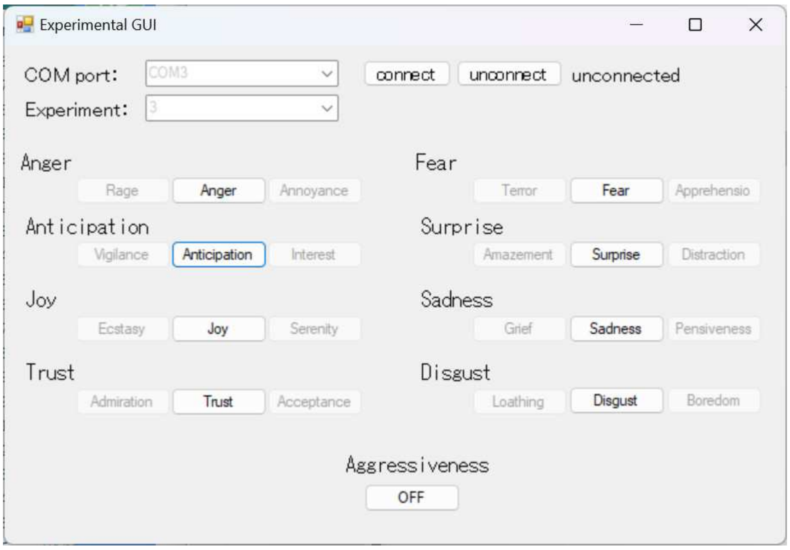

FIGURE 3. GUI for color control for Experiment 3

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.

4.2. **Model of emotions.** Following the approach outlined by [39], 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.

4.2.1. *Model for basic emotion expressing using color.* This model exclusively utilizes colors to represent the 8 basic emotions outlined in Table 3. Upon activation, the robot exhibits the color associated with the selected emotion and maintains this color consistently until it is either turned off or switched to a different color.

4.2.2. *Model for basic emotion intensity expressing using color blinking.* This model is structured to express emotions intensity through designated colors and two 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 two blinking rates and ask which one represents higher emotion intensity;
- Ensuring that all emotions are visually distinguishable from one another.

4.2.3. *Model for dyads expressing using color gradient.* 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

Table 3. The model of 24 primary emotions

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

second mimics a sinusoidal waveform. Specifically, the calculation for the RED component is as follows:

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

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

$$\text{WAIT} = \frac{\text{PERIOD1} - \text{PERIOD2}}{360}, \tag{2}$$

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.**

Three experiments were developed to assess the effectiveness of color-based models in conveying emotions and dyads within a Vietnamese context. The following provides an overview of each experiment:

Experiment 1: This experiment examines the effectiveness of a model that solely relies on colors to represent emotions.

Experiment 2: This experiment examines the effectiveness of a model that relies on colors and blinking rates to represent lower or higher intensity emotions.

Experiment 3: This experiment assesses the effectiveness of a model that utilizes color gradients to express dyads.

The results are then compared with findings from previous studies on color-based models in a Japanese context [38, 39] to enable a comprehensive analysis of cultural differences in color-based methods. By examining how emotions are mapped to colors across Vietnamese and Japanese populations, this study aims to highlight subtle cultural distinctions in emotional perception and expression. Such comparisons contribute to a deeper understanding of how color-based methods can be adapted to align with the cultural context of different user groups, enhancing the effectiveness of these models in cross-cultural applications.

5.1. **Participants.** As a research investigated in the influence of color-based model in different contexts, participants involved in experiments are Vietnamese individuals aged between 18 and 24, with a gender distribution of 51.8% male and 48.2% female, and all participants had no known visual impairments. 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. Participants are encouraged to complete the tasks at their convenience and in a quiet environment conducive to concentration. To minimize biases from prior knowledge or assumptions, separate sets of participants are used for each experiment. In total, approximately 600 participants take part across three experiments. They are presented with video recordings of robots displaying various emotion, blinking rates and dyad models scenarios and are then asked to respond to the provided questions.

5.2. **Experiment design.** In the three experiments, we examined the efficacy of utilizing color, blinking, and gradients as means for robots to convey emotions and dyads, specifically focusing on comparing Vietnamese and Japanese cultural perceptions.

In Experiment 1, each emotion was associated with a specific color, and participants were asked to identify the emotion conveyed by the robot's color display. Initially, the robot presented one color corresponding to a basic emotion (Anger, Anticipation, Joy, Trust, Fear, Surprise, Sadness, or Disgust). Participants were then shown a set of eight emotions and asked to rate how likely each emotion was being expressed, using a scale from 0 to 5, where 0 meant "least likely" and 5 meant "most likely". For example, when the robot displayed the color red, a participant might rate 5 for Anger, 3 for Disgust, 2 for Fear, and 0 for all other emotions.

In Experiment 2, following [39], each emotion has two videos with two blinking rates which are slow and fast. Participants were tasked with identifying the emotions' intensity conveyed by the blinking colors exhibited by the robot. Participants were provided with information about the basic emotions (e.g., Anger, Joy, and Fear) and were then required to determine which rate indicates the higher intensity. There were a total of 8 questions each with 2 videos, corresponding to 8 groups of extended emotions. The blinking rate was adopted from [39] to ensure comparability, as their findings indicated that Japanese participants perceived higher blinking rates as signals of more intense emotions.

In Experiment 3, following [38], we utilized color gradients to represent the eight primary dyads. 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. The transition speed between colors was also kept consistent with these prior studies to isolate cultural differences in color perception without introducing variability from temporal changes in emotion display.

6. Experimental Results.

6.1. **Experiment 1.** The experimental findings for Experiment 1 are presented in Figure 4. This heatmap illustrates the average ratings assigned to each emotion by 311 and 21 participants for Vietnamese and Japanese contexts, respectively. The y-axis corresponds to the intended emotion (studied emotions), while the x-axis represents the participants' interpretations (evaluation emotions).

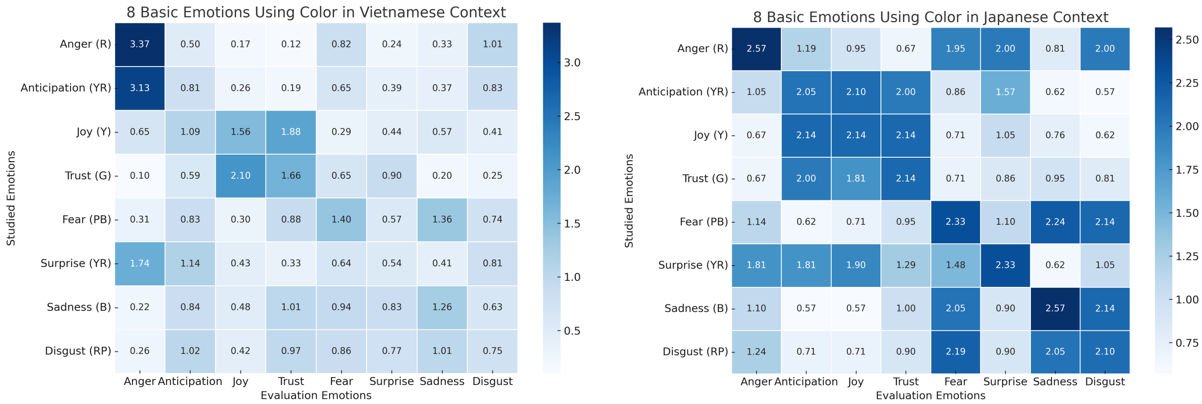

FIGURE 4. Comparison of emotion recognition by color in Vietnamese and Japanese contexts. The y-axis represents the intended emotions (the emotions assigned to specific colors in the study), where R, YR, Y, G, PB, YR, B, and RP stand for Red, Yellow Red, Yellow, Green, Purple Blue, Yellow Red, Blue, and Red Purple, respectively. The x-axis represents the participants' chosen emotion ratings. The intensity of each cell reflects the average rating given by participants for each color cue, with darker colors indicating stronger agreement. For example, the first cell (3.37) means that, on average, participants rated 3.37 out of 5 for the likelihood that when the robot displayed red, it was expressing anger.

The heatmaps for the Vietnamese and Japanese contexts present a comparison of how participants in each culture interpreted basic emotions based on color-based cues displayed by a robot.

Overall, the Vietnamese heatmap shows more variability along the diagonal, with fewer values as prominently high. For instance, emotions like Surprise and Disgust in the Vietnamese context do not have strong diagonal values, which may imply that participants in the Vietnamese sample had difficulty associating these colors with the intended emotions. While Anger and Joy have relatively high values on the diagonal – 3.37 and 1.56, respectively – the pattern overall lacks the uniformity observed in the Japanese context. In contrast, in the Japanese heatmap, we observe that the diagonal values – particularly for Anger (2.57), Anticipation (2.05), Joy (2.14), Trust (2.14), Fear (2.33), Surprise (2.33), Sadness (2.57), and Disgust (2.1) – are generally high. This trend suggests a stronger or more consistent association of these colors with the intended emotions. Such high diagonal values imply that Japanese participants were more aligned with the intended emotional representations conveyed by the colors. One of the possible reasons here might be the cultural or cognitive familiarity with color-emotion associations, possibly influenced by Japan's societal norms, artistic traditions, or media representations that emphasize clear emotional associations with colors. For instance, Japanese culture often uses distinct color symbolism in visual arts, anime, and traditional ceremonies, which may contribute to a more standardized perception of colors in emotional contexts.

The heatmaps indicate that certain emotions exhibit high intensity across both cultural contexts. For example, Anger shows elevated values in both groups (Vietnamese: 3.37, Japanese: 2.57), suggesting a strong and consistent recognition or association of Anger with its designated color cues. However, significant cultural variations emerge in the perception and intensity of other emotions. Anticipation, for instance, elicits a notably stronger response among Japanese participants (2.05) compared to Vietnamese participants (0.81), implying that Japanese individuals may interpret colors representing anticipation more consistently or intensely, while Vietnamese participants often confuse it with Anger (3.13). Similarly, Fear displays a higher intensity within the Japanese context, which may reflect a clearer or more culturally resonant understanding of the emotion's color representation among Japanese participants.

Overall, the data suggest that, although some universal patterns in emotional recognition from color cues are present, notable cultural differences exist. Japanese participants, for example, demonstrate heightened sensitivity to colors associated with Anticipation and Fear. The model's stronger performance in Japan underscores the importance of cultural alignment in enhancing the effectiveness of emotion recognition systems, highlighting the need to adapt such models to specific cultural contexts.

To evaluate how participants rated emotions based on color cues, we conducted a repeated measures ANOVA. Emotion category (Anger, Anticipation, Joy, Trust, Fear, Surprise, Sadness, Disgust) was included as a within-subject factor, as each participant rated multiple colors. The dependent variable was emotion rating (scale: 0-5). Due to computational constraints, the analysis was performed on a random subset of 100 participants while preserving the overall data structure. The significance threshold was set at $p < 0.05$, and Greenhouse-Geisser corrections were applied when sphericity assumptions were violated.

The repeated measures ANOVA revealed a significant main effect of studied emotion, $F(7, 693) = 15.24$, $p < 0.0001$, indicating that different colors elicited different emotion ratings. The main effect of rated emotion was also significant, $F(7, 693) = 380.92$, $p < 0.0001$, suggesting that certain emotions were perceived more distinctly than others. Additionally, there was a significant interaction between studied emotion and rated emotion, $F(49, 4851) = 524.44$, $p < 0.0001$, confirming that the way emotions were associated with colors influenced how participants assigned ratings. This aligns with heatmap findings, where some color-emotion pairs (e.g., Red $\rightarrow$ Anger) were strongly recognized, while others showed confusion.

6.2. **Experiment 2.** The results of Experiment 2 are illustrated in Table 4. These tables show the percentage of participants who chose a fast or slow blinking rate to represent the higher intensity emotion, given by 111 and 21 participants, in Vietnamese and Japanese contexts, respectively.

The results of Experiment 2 underscore significant cultural differences in interpreting emotional intensity. A distinct pattern emerged: while Japanese participants predominantly associated faster blinking with higher intensity across most emotions, Vietnamese participants leaned toward perceiving slower blinking as a stronger indicator of intensity, particularly for certain emotions.

Table 4. Emotion intensity comparison: Vietnamese and Japanese contexts (Higher Emotion Intensity). "*" are emotions where the percentages of slow rate chooser is higher than the fast rate.

Vietnamese context			Japanese context		
Emotion	**Fast (%)**	**Slow (%)**	**Emotion**	**Fast (%)**	**Slow (%)**
Anger	70.1	29.9	Anger	100	0
Anticipation*	48.11	51.89	Anticipation	85.71	14.29
Joy	54.64	45.36	Joy	76.19	23.81
Trust	56.99	43.01	Trust	61.9	38.1
Fear*	35.71	64.29	Fear	57.14	42.86
Surprise*	29.47	70.53	Surprise	66.67	33.33
Sadness*	32.32	67.68	**Sadness***	23.81	76.19
Disgust*	35.42	64.58	Disgust	66.67	33.33

In the Japanese context, a clear trend shows that participants identified faster blinking as indicating higher intensity across the majority of emotions. For example, Anger reached 100% intensity when blinked at a fast rate, with no association of intensity with the slow rate. Similarly, emotions like Anticipation (85.71% fast) and Joy (76.19% fast) also showed strong preferences for fast blinking to convey high intensity. These results suggest that Japanese participants view faster, more dynamic cues as signaling heightened emotional states, which may be influenced by cultural norms valuing outward expressions of intensity. The consistent correlation between fast blinking and high intensity across the Japanese data implies that participants share a culturally reinforced interpretation of blink rate as an active indicator of emotional strength.

In contrast, Vietnamese participants associated slower blinking with higher intensity in several key emotions. This is especially notable for Surprise and Sadness, where 70.53% and 67.68% of participants, respectively, associated the slow blink rate with a higher emotional intensity. This trend extends to other introspective or passive emotions, indicating that Vietnamese participants may perceive slower, more prolonged cues as better representations of deep, intense emotions. Emotions like Disgust (64.58% slow) and Fear (64.29% slow) also exhibit this pattern, suggesting that Vietnamese participants might interpret slower blinking as conveying a more reflective or contemplative form of emotional expression, possibly due to cultural inclinations towards subtlety in emotional display.

The overall effectiveness of the blinking model is notably context-dependent, performing more predictably in Japan where fast rates consistently signify high intensity. In Japan, the model's alignment with fast blinking as a cue for heightened emotion creates a more uniform pattern across various emotions, enabling clearer communication of intensity. However, in Vietnam, the variability in preferred blink rates across emotions indicates that a universal fast-blinking approach does not achieve consistent results. Instead, the preference for slow blinking to represent high intensity in emotions suggests that Vietnamese participants may find slower cues more compatible with certain emotional states, especially those linked to contemplation or restraint.

These findings emphasize the importance of culturally adapted design for emotional communication in human-robot interaction. In Japanese contexts, robots might effectively convey intensity through fast blinking, reinforcing Japanese participants' interpretation of active blinking as a sign of strong emotion. For Vietnamese audiences, however, a different strategy would be beneficial: leveraging slow blinking for emotions like Sadness and Fear could enhance the naturalness and interpretability of the robot's emotional cues, fostering more authentic engagement.

To determine whether participants exhibited a significant preference for Fast or Slow blinking rates in emotion intensity perception, we conducted a Chi-Square Goodness-of-Fit test. Each emotion was tested separately, with an expected 50%-50% distribution assuming no preference. The significance level was set at $p < 0.05$.

The analysis revealed significant preferences for certain emotions.

- Anger was perceived as more intense with Fast blinking $\chi^2(1) = 16.16$, $p < 0.0001$.
- Fear, Surprise, Sadness, and Disgust were perceived as more intense with slow blinking (all $p < 0.01$).
- Anticipation, Joy, and Trust did not show a significant preference ($p > 0.05$), suggesting that participants did not strongly associate either rate with intensity for these emotions.

These results suggest that blinking rate influences emotion intensity perception, with Fast blinking being linked to high-arousal emotions (e.g., Anger), while slow blinking was associated with emotions such as Fear and Sadness.

6.3. **Experiment 3.** Figure 5 provides a summary of the experimental results for Experiment 3. The heatmaps display the average scores assigned by 176 Vietnamese and 21 Japanese participants for each dyad. In these visuals, the y-axis represents the intended dyads (studied dyads), and the x-axis shows the dyads as interpreted by participants (evaluation dyads). In Experiment 3, participants across Vietnamese and Japanese contexts rated eight primary emotional dyads represented by color gradients on a five-point scale. Analysis of the heatmaps reveals notable differences in the perception and rating patterns for each dyad between the two cultural contexts.

Overall, certain dyads, such as Love, Aggressiveness, and Optimism, consistently receive high ratings across both cultural contexts.

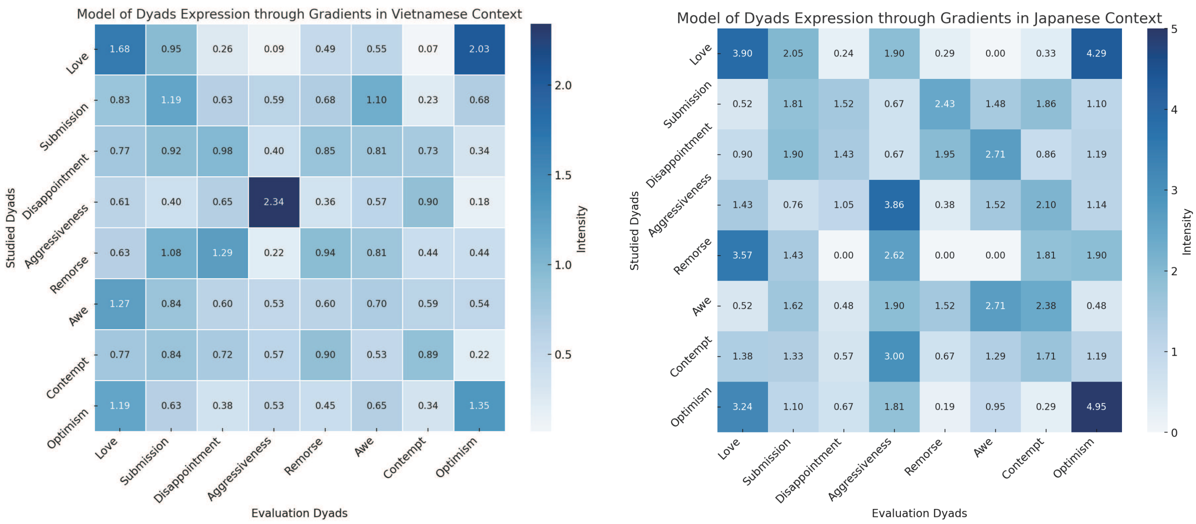

Figure 5. Comparison of model of dyad expression in Vietnamese and Japanese contexts. The y-axis represents the studied dyads (the dyads assigned to specific colors gradient in the study). The x-axis represents the participants' chosen dyad ratings. The intensity of each cell reflects the average rating given by participants for each color gradient cue, with darker colors indicating stronger agreement. For example, the first cell (1.68) means that, on average, participants rated 1.68 out of 5 for the likelihood that when the robot displayed gradient between Yellow (Joy) and Green (Trust), it was expressing Love.

In the Vietnamese context, we observe that dyads like Love and Optimism receive relatively high ratings (e.g., Love with 1.68 for the Love dyad and Optimism at 2.03), suggesting that these emotions align well with the color gradients presented. However, more introspective dyads, such as Contempt and Disappointment, generally receive lower scores, indicating less alignment or interpretive difficulty in linking these emotions with color gradients. Vietnamese participants rated Aggressiveness (2.34) significantly high, suggesting that vibrant or intense color gradients are easily associated with high-energy emotions.

In contrast, the Japanese heatmap shows that participants provided higher ratings for a broader range of dyads, indicating a more uniform interpretation of the color-emotion associations. For example, Love (3.9), Optimism (4.95), and Aggressiveness (3.86) received high ratings, reflecting strong identification with these dyads. This trend suggests that Japanese participants may have more culturally consistent interpretations of emotions represented by color transitions. Moreover, ratings for introspective or complex emotions such as Remorse and Contempt were higher in Japan compared to Vietnam, indicating that Japanese participants may be more receptive to these nuanced color-emotion pairings or have a more versatile framework for interpreting emotional colors.

Overall, the model appears to function more effectively in the Japanese context, where participants provided higher, more uniform ratings, implying clear and consistent associations between color gradients and emotional dyads. This may stem from cultural influences, such as the prominence of color symbolism in Japanese visual culture, which could reinforce associations between color and emotional expression. Conversely, the Vietnamese context shows greater variability, with only certain emotions like Love and Aggressiveness being strongly aligned with color gradients, suggesting that cultural factors may influence how colors are interpreted in terms of emotional intensity and type.

To assess how participants rated dyads based on color gradients, we also conducted a Repeated Measures ANOVA for this experiment. The emotion dyad category (Love, Submission, Disappointment, Aggressiveness, Remorse, Awe, Contempt, Optimism) was included as a within-subject factor. The dependent variable was the emotion intensity rating (scale: 0-5). Due to computational constraints, a random subset of 100 participants was analyzed while maintaining the overall data structure. The significance threshold was set at $p < 0.05$.

The repeated measures ANOVA revealed a significant main effect of studied dyad, $F(7, 693) = 11.75$, $p < 0.0001$, indicating that different dyads elicited different emotion ratings. The main effect of rated dyad was also significant, $F(7, 693) = 160.20$, $p < 0.0001$, suggesting that certain dyads were rated more distinctly than others. Additionally, there was a significant interaction between studied dyad and rated dyad, $F(49, 4851) = 225.54$, $p < 0.0001$, confirming that the way dyads were associated with colors influenced how participants assigned ratings. This aligns with heatmap findings, where some dyad pairs (e.g., Aggressiveness $\rightarrow$ Aggressiveness) were strongly recognized, while others showed confusion.

7. Discussion.

7.1. Experiment results discussion.

In Experiment 1, these findings indicate that cultural factors may influence the perception of emotional colors, likely due to varying cultural experiences and interpretations of emotional expression. This analysis suggests that the color-based model would be more effective in Japan than in Vietnam. For future implementations in robot design, especially for emotionally responsive robots, adapting the color-based model to fit cultural contexts could enhance user interaction. Robots programmed for a Japanese audience, for instance, might emphasize the emotional colors associated with anticipation and fear, while those designed for Vietnamese users might focus on emotions like anger and sadness, where there is strong recognition in both contexts. These insights underline the importance of culturally adaptive interfaces in affective computing and social robotics. For Japanese users, color cues alone might be sufficient to communicate a range of emotions effectively. However, for Vietnamese users, supplementary modalities – such as facial expressions, sound cues, or movement – may be necessary to enhance emotional recognition.

In Experiment 2, while the color-based blinking model works more uniformly in the Japanese context, with fast rates conveying high emotional intensity, adapting the model for Vietnamese users to highlight slow blinking for certain emotions could provide a richer, culturally resonant interaction experience. This study underscores the need for culturally nuanced approaches in affective computing, particularly in designing emotion-expressive robots, to ensure effective communication across diverse cultural landscapes.

In Experiment 3, the color gradient model demonstrates greater efficacy in the Japanese context, where ratings reflect a stronger consensus around color-emotion pairings. For practical applications, robots designed for Japanese audiences could leverage these color gradients with confidence that a range of emotions will be accurately interpreted. In Vietnamese settings, however, additional cues or adjustments to color gradient designs might be required to enhance interpretability, especially for more complex emotions like Contempt or Remorse. These findings emphasize the importance of cultural adaptation in affective computing, supporting the development of more intuitive, emotionally expressive interfaces across diverse cultural contexts.

7.2. **Cultural differences analysis.** The observed differences in emotion recognition consistency between Japanese and Vietnamese participants can be explained through Hofstede's cultural dimensions theory [50, 51]. Specifically, two key dimensions – Uncertainty Avoidance and Collectivism vs. Individualism – may account for the greater consistency observed in Japanese responses.

Firstly, Japan ranks high in uncertainty avoidance, meaning that Japanese individuals tend to prefer structured, predictable environments and clear categorizations [51]. This cultural trait may contribute to Japanese participants interpreting emotional expressions more uniformly, as they are more likely to rely on established social conventions in emotion recognition. In contrast, Vietnam has a lower uncertainty avoidance score, suggesting that Vietnamese participants may be more flexible in their interpretations, leading to greater variability in their responses to color-based emotional cues.

Secondly, Japan is a more collectivist society than Vietnam, meaning that social harmony and shared interpretations of emotions are emphasized in daily communication [50]. This may explain why Japanese participants show higher agreement in associating colors with emotions, as they likely internalize a more standardized cultural framework for emotional expression. Meanwhile, Vietnam, while also collectivist, has historical and regional variations in emotional communication that may contribute to less uniformity in emotional associations. These cultural factors provide a plausible explanation for the differences observed in our study. Future research could further investigate how cultural dimensions influence emotion recognition consistency by incorporating additional countries with varying levels of uncertainty avoidance and collectivism to validate these findings.

7.3. **Future directions.** While our results indicate that the color-based emotion model performs better in the Japanese context, it exhibits greater variability in Vietnamese participants' responses. To address this, we propose incorporating supplementary multimodal cues to strengthen emotion recognition in the Vietnamese context.

First, visual enhancements could improve recognition by making emotional expressions more dynamic and contextually salient. Adjusting the transition speed and brightness variations of colors may help Vietnamese participants, who may rely on dynamic changes rather than static color associations alone. Additionally, integrating animated facial expressions or robot gestures alongside color transitions could reinforce emotional cues, making them easier to interpret.

Second, auditory cues could enhance emotion recognition by providing additional context through sound. Previous studies suggest that tone, pitch, and vocal expressions influence emotion perception across cultures. Therefore, incorporating emotion-congruent sound effects (e.g., rising pitch for anticipation, and lower tone for sadness) could provide reinforcement for emotion interpretation. Additionally, verbal emotion labels or culturally relevant vocal feedback could help clarify emotions for Vietnamese participants, who may require more explicit contextual information than their Japanese counterparts.

By integrating these multimodal enhancements, the model can become more adaptable across cultures while maintaining its effectiveness. Future research should explore how different combinations of visual and auditory cues influence emotion perception in diverse user groups, ensuring that human-robot interactions remain intuitive and culturally appropriate.

7.4. **Limitations.** This study significantly improves upon previous research by achieving a more balanced gender distribution and increasing the sample size to approximately 600 participants, enhancing the reliability and generalizability of our findings. These improvements ensure that our results more accurately reflect gender-inclusive interpretations of color-emotion associations in both Vietnamese and Japanese contexts. However, one remaining limitation is the age range of participants, as the study primarily focuses on younger individuals. While this demographic is particularly relevant given its frequent interaction with human-robot interfaces and digital communication, color perception and emotional associations may vary across age groups due to differences in cultural exposure, generational shifts, and lived experiences. Future research should explore how older Vietnamese and Japanese participants perceive color-emotion relationships to determine whether these findings extend across different age demographics. Additionally, examining potential age-gender interaction effects could further refine the applicability of color-based emotion models for diverse user groups in human-robot interaction.

8. **Conclusion.** This research explored the effectiveness of color-based emotion models across Vietnamese and Japanese cultural contexts, with a focus on assessing variations in emotional recognition, intensity perception, and dyad interpretation. The results demonstrated that while certain universal patterns in color-emotion associations exist, distinct cultural differences significantly impact how emotions are perceived and interpreted through color cues. Japanese participants showed higher consistency in recognizing and responding to color-emotion associations, suggesting a stronger cultural alignment with the model's structure, while Vietnamese participants exhibited more variability, particularly in interpreting emotion intensity through blinking rates and complex dyads.

These findings underscore the importance of culturally adaptive models in human-robot interaction, as the effectiveness of emotion expression mechanisms can vary across cultural boundaries. For practical applications, color-based models designed for Japanese users may require minimal modification, but models aimed at Vietnamese audiences could benefit from supplementary cues, such as movement or additional sensory inputs, to enhance clarity in emotional communication.

While this study focuses on Japanese and Vietnamese cultural differences in color-based emotion recognition, its findings have broader implications for cross-cultural human-robot interaction. The observed variations highlight the need for adaptive emotion models that accommodate cultural differences in emotion perception. Future research should explore how these models generalize to other cultures and whether multimodal enhancements (e.g., facial expressions, voice, or gestures) can improve emotion recognition across diverse user groups. These insights contribute to the development of more intuitive and culturally aware robots, ensuring effective emotional communication in global contexts.

Overall, this research contributes to the field by highlighting the role of cultural context in emotion recognition models and setting a foundation for future studies focused on refining cross-cultural human-robot interaction design.

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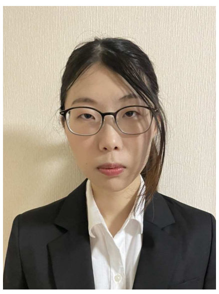

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