

# Emotional Expression and Mental Health: Decoding Color and Drawing Styles with Python and OpenCV

## Abstract

**Introduction:** Despite advancements in understanding color-emotion correlations, the influence of mental health on this relationship is less studied. Our research explores how mental health impacts emotional expression through color and depiction style. **Methods:** Engaging 212 students, we collected 1272 digital drawings representing six primary emotions: anger, fear, sadness, calm, excitement, and happiness. Our study, conducted from November to December 2023, utilized a cross-sectional design. Participants were recruited through convenience sampling. We collected both survey responses and participant-generated images. Using Python and OpenCV, we quantified subjective emotional expressions. **Results:** Participants predominantly chose red for anger (57.43%), illustrating the red usage percentage for anger, black for fear (38.14%), gray and blue for sadness (27.86%, 27.83%), green for calm (25.73%), and red for both excitement (27.26%) and happiness (22.85%). Fear was the most frequent color fill at 31.58%, with anger the least at 24.95%. Tangible imagery was prevalent (88%–96.2%), while abstract styles were most common in fear depictions (12%). Emotion significantly influences color choices ( $P = 0.017$ – $<0.001$ ), color number ( $P < 0.001$ ), and image coverage ( $P = 0.003$ ). Drawing style comparisons across three mental health levels showed minimal yet significant usage differences: black for fear ( $P = 0.037$ ), color variability ( $P = 0.027$ ), and purple for calm ( $P = 0.012$ ). Despite these differences, mental health did not significantly moderate the relationships between color use and drawing styles. **Conclusion:** Our study advanced color-emotion research by letting participants select colors, highlighting minimal mental health impacts on emotional expression and consistent associations across cultures and ages. Using Python and OpenCV to quantify qualitative images has greatly increased analysis objectivity, substantially progressing the field.

**Keywords:** Color, drawing styles, emotional expression, mental health

## Introduction

Previous studies have extensively explored the connection between color and emotion. For instance, the Manchester Color Wheel study demonstrated how participants associated specific colors with their moods; yellow indicated happiness and excitement, while blue was linked to sadness and calmness.<sup>[1]</sup> This association is further evidenced in various contexts, such as Pablo Picasso's *The Old Guitarist*, where he employs icy blues and somber tones to depict his grief during a period marked by poverty and the death of a friend.<sup>[2]</sup> Similarly, Jonauskaitė *et al.* utilized a computerized color picker, allowing participants to select colors that represented their emotions while engaging with different media. They found that yellow often corresponded with joy,

whereas achromatic colors were associated with sadness.<sup>[3]</sup>

The literature also identifies consistent associations across different studies, linking red with anger and love, pink with love, and various shades such as white, gray, and black with feelings ranging from relief to sadness and fear.<sup>[3-7]</sup> Further research has connected hues, lightness, and chroma with specific emotions – yellow with joy, yellow-green with relaxation, and lighter shades with positivity.<sup>[3]</sup> Their subsequent study highlighted age-specific differences in color-emotion associations, revealing that older adults tend to have more positive and specific color reactions than adolescents.<sup>[6]</sup> Despite these significant insights, the influence of mental health on how color and style modulate emotional expression remains underexplored, suggesting a pivotal area for future research.

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Research has long categorized emotions as either positive or negative, introducing models such as the circumplex model of affect, which defines emotions along two dimensions: valence and arousal.<sup>[7,8]</sup> Valence and arousal refer to all affective states arising from two fundamental neurophysiological systems; valence is related to a positive pleasure – negative displeasure continuum, and arousal is related to a high activation – low activation continuum.<sup>[7,8]</sup> This valence-arousal model allows for classifying emotions such as happiness, associated with positive valence and high arousal, and sadness, anger, and fear, characterized by negative valence with varying arousal levels. Further investigations into the emotional impacts of color revealed that highly saturated blue evoked higher valence, while red was the most arousing color.<sup>[9]</sup> Elliot highlighted consistent relationships between colors and emotions, identifying a positive relationship between red and excitement and green with calmness.<sup>[10]</sup> Similarly, a study involving artists and nonartists showed a universal tendency to use red to express anger and blue for sadness, suggesting a common perceptual link between specific colors and emotions.<sup>[11]</sup>

Elliot's approach and avoidance theory further elucidate that human motivation is driven by the desire to approach positive and avoid negative outcomes, impacting a wide range of behaviors and psychological responses. This theory suggests that negative emotions typically trigger avoidance behaviors, while positive emotions encourage approach actions.<sup>[12]</sup> Recent research delves into the relationships between artistic expression and psychological states. Significant correlations were found between the dynamics of movement and contour in artwork and clients' mental health.<sup>[13]</sup> Another study used graphic elicitation with college students to explore happiness in leisure, connecting it to specific times, spaces, and activities.<sup>[14]</sup> Moreover, a groundbreaking study employed computational analysis to decode emotions in abstract drawings, finding that nonartist works provided more precise emotional expression than those of artists.<sup>[11]</sup>

Advancements in technology have enhanced emotion recognition research by streamlining data gathering and emotion identification with minimal disruption to participants. One study focused on drawing strokes to understand cognitive states.<sup>[15]</sup> Another examined how 12 colors relate to 20 emotions among 711 individuals from four countries, including China, Germany, Greece, and the UK, uncovering universal and culturally specific color-emotion associations through machine learning

analysis.<sup>[16]</sup> Additionally, a study utilized the Emothaw database to identify depression, anxiety, and stress through handwriting and drawings, achieving significant detection rates with a radial basis support vector machine model.<sup>[17,18]</sup> A recent study linked stroke count in drawings to depression severity.<sup>[19]</sup> These studies demonstrate the varied approaches and effectiveness of using nonverbal cues for emotion recognition.

Most studies examine how mental health is reflected in drawings, but few explore the factors affecting the color-emotion link. This research focuses on the impact of mental health on visual and emotional expression through art, specifically examining the elements of color and style used by students to depict a range of emotions. To address gaps in the literature and enhance authenticity, this study adopted participant-generated visual methods<sup>[20]</sup> to examine the visualization of six primary emotions – anger, fear, sadness, calm, excitement, and happiness – in drawings, aiming to test the hypothesis outlined in Figure 1.

- Hypothesis 1: Emotional expression in drawings differed significantly based on styles, including color use, spatial allocation, and depiction styles
- Hypothesis 2: Mental health status directly affected the visual representation of emotions in drawings
- Hypothesis 3: Mental health status had a moderating effect on the visual representation of emotions in drawings.

## Methods

### Study design

Our study, conducted from November to December 2023, utilized a cross-sectional design.

### Setting

The study was conducted among students from elective courses without color vision deficiencies in Thailand.

### Participants

Participants were recruited through convenience sampling. Initially, we received samples from 240 participants, reduced to 212 after removing unreadable or incorrect images.

### Data sources/measurement

Instructions emphasized individual documents for each emotion, disregarding artistic skill in favor of genuine

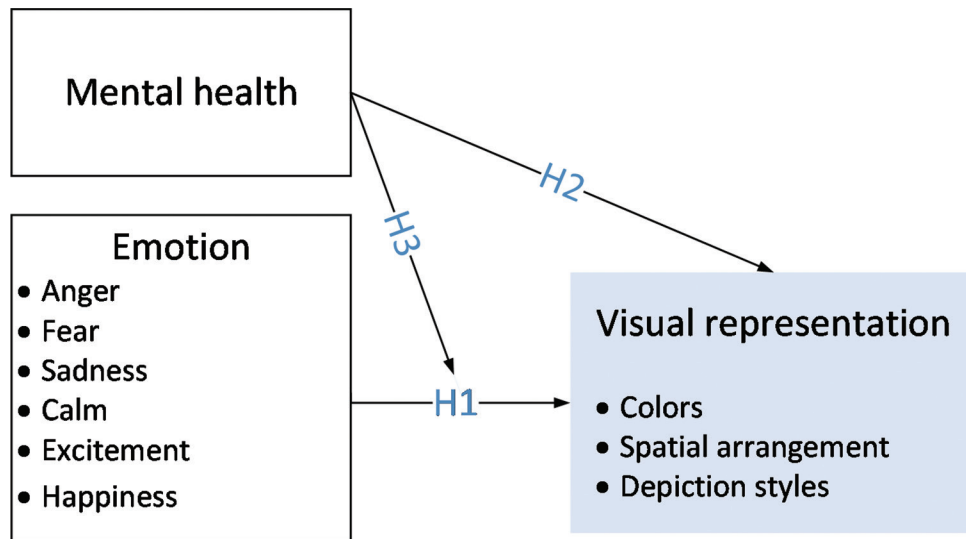


Figure 1: Hypothesized framework

emotional expression and completion within 30 min. Surveys on their drawings were also collected. Digital informed consent was obtained from all, with privacy maintained through anonymization before analysis.

### Mental health

Mental health was evaluated using the Brief Symptom Rating Scale (BSRS-5),<sup>[21]</sup> a screening tool with a Cronbach's alpha of 0.824 in this study, for detecting psychiatric conditions. It features a scale from 0 (not at all) to 4 (extremely) for items. BSRS-5 includes five questions: (1) trouble falling asleep, such as difficulty falling asleep, waking up easily or waking up early; (2) feeling tense or keyed up; (3) feeling easily annoyed or irritated...; (4) feel blue; and (5) feeling inferior to others. We categorized samples into three levels of psychiatric condition based on the average scores of five BSRS-5 (mean = 1.78, standard deviation [SD] = 0.91) items: Level 1 (minor,  $\leq 1$ ), Level 2 (moderate, 1–2.2), and Level 3 (severe,  $\geq 2.2$ ).

### Image data

Our study used Python<sup>[22]</sup> (version 3.10) and OpenCV<sup>[23]</sup> (version 4.8.0.74) to analyze image color profiles. Python's readability and flexibility made it suitable for data analysis, while OpenCV's comprehensive image processing tools allowed for efficient image processing and conversion to appropriate color spaces. We utilized the hue, saturation, and value (HSV) color space,<sup>[24]</sup> providing a more intuitive representation of colors compared to red, green, and blue. This model focuses on hue, saturation, and brightness, with hue on a circular scale and saturation and value denoting color intensity and brightness, respectively. For compatibility with digital graphics, we normalized HSV values to fit 8-bit channels, adjusting Hue to 0–180 and keeping S and V at 0–255 using Python and OpenCV. This standardization ensured consistent color representation across various software platforms.

Detailed explanations of the general HSV ranges and their specific adjustments for OpenCV and data are available from the corresponding author upon reasonable request. This data has been coded and permanently de-identified. All data were accessible via the following web link: [https://osf.io/cv3hd/view\\_only=0d918eb57b7146cbbf0cd36938a511bb](https://osf.io/cv3hd/view_only=0d918eb57b7146cbbf0cd36938a511bb).

Key variables through OpenCV and Python are defined as follows:

1. Color percentage: Measures the extent of a specific color within an image, calculated by the percentage of pixels that match the specified color relative to the total pixels
2. Number of colors used: Seven colors were employed on the digital canvas for expressive purposes, with white excluded as it signifies a blank canvas
3. Color fill percentage: Indicates the proportion of the canvas covered by color
4. Image coverage percentage: Represents the portion of the canvas covered by the subject, including any internal blank spaces.

### Styles of emotional depictions

Participants' images ranged from realistic to abstract, posing challenges for algorithmic recognition and quantification. Three assistants categorized the varied content and depiction styles for analysis. Respondents' drawings representing six emotions were categorized as tangible or abstract. Tangible emotion depictions in drawings feature identifiable content, such as specific shapes or figures, while abstract styles may appear as lines, circles, or other less directly interpretable forms.

### Bias

Efforts were made to minimize bias by anonymizing the data before analysis and by standardizing the instructions given to participants.

## Sample size estimation

Initially, we received samples from 240 participants, reduced to 212 after removing unreadable or incorrect images. Participants, all students from elective courses without color vision deficiencies, created drawings to express six emotions – anger, fear, sadness, calm, excitement, and happiness – using a blank digital file on their smartphones. Totally 1272 drawings and images were analyzed by employing Python and OpenCV.

## Statistical analysis

IBM Corporation, Armonk, New York, USA. IBM SPSS Statistics 27.0.0 v. 27. <https://www.ibm.com/docs/en/spss-statistics/27.0.0> (2021). we performed descriptive statistics to explore participant characteristics and themes in drawings of six emotions. To examine how emotional expressions varied by mental health, we applied Chi-square, ANOVA, *post hoc* LSD tests, and multivariate analyses.

## Ethical consideration

This study, approved by the National Cheng Kung University Human Research Ethics Committee (HREC 112-5265), adhered to strict ethical standards and regulations.

## Results

In total, we initially received samples from 240 participants. After excluding unreadable or incorrectly sent images, we ultimately included 212 participants and 1272 drawing images in our final analysis. All participants were screened for color vision deficiencies, with no such conditions found among the students.

As shown in Table 1, the study participants consisted of 212 individuals with an average age of 20.17, ranging from 19 to 25. Gender distribution includes 78 females (36.8%) and 134 males (63.2%). All participants are undergraduates. The majority are in the field of Sport Science (80.66%), followed by Public Health and Nursing (17.45%), and Others (1.89%).

Table 2 displays the significant differences in color percentage, and number of colors used across six emotions ( $P < 0.001$ ), with no significant differences in

color-filled percentage and image coverage. Based on the average usage percentages of colors in images [Figure 2], the most commonly used color for the emotion of anger was red (mean = 57.43%, SD = 40.3). Fear's frequently selected colors included black (mean = 38.14%, SD = 30.8). Sadness was typically depicted using gray (mean = 27.86%, SD = 31.09) and blue (mean = 27.83%, SD = 39.27). Excitement and happiness had red (mean = 27.26%, SD = 36.02; mean = 22.85%, SD = 33.13) as the predominant choice. Fear had the highest color fill percentage of the six emotions at 31.58%, while anger recorded the lowest at 24.95%.

Comparison of drawing styles across three mental health levels showed significant differences in the use of black for depicting fear ( $P = 0.037$ ) and in color-filled percentage ( $P = 0.027$ ), as well as in the use of purple for calm ( $P = 0.012$ ). In a comparative study on mental health levels and color use for “anger,” severe-level participants showed less red usage compared to those at minor and moderate levels (means: 54.24 vs. 66.88 and 53.79) but significantly increased their blue usage over minor level (means: 3.27 vs. 0.35,  $P = 0.05$ ) and used more gray than minor (means: 18.07 vs. 1.03,  $P = 0.04$ ). Those at the moderate level used more blue for “fear” than at the minor level (mean: 7.28 vs. 1.12,  $P = 0.042$ ) and recorded higher color fill percentages than the severe level (means: 35.21, 35.74 vs. 24.74,  $P = 0.029, 0.016$ ). For sadness, severe-level participants had greater image coverage than moderate-level participants (mean: 76.78 vs. 69.96,  $P = 0.047$ ). At calm, severe levels used a notably higher amount of purple than minor and moderate (mean: 5.82 vs. 0.77 and 0.1,  $P = 0.021$  and  $P = 0.006$ ). For excitement, less yellow was used by the severe level than the moderate (mean: 7.78 vs. 9.72,  $P = 0.045$ ).

Table 3 classifies respondents' emotional depictions into two categories across six emotions. Tangible styles dominated at 87.98%–96.21%, while abstract styles peaked for fear (12%) and dipped for happiness (3.8%). Significant differences were observed among the four tangible emotion styles ( $P < 0.05$ – $0.001$ ).

Multivariate analyses reveal that emotion significantly affects color choices ( $P < 0.001$ ), the number of colors ( $P < 0.001$ ), and image coverage ( $P = 0.003$ ); details are not shown here. Mental health minimally affected the use of red ( $P = 0.027$ ), gray ( $P = 0.034$ ), and color fill percentage ( $P = 0.008$ ). There was no significant moderating effect of mental health on color and drawing style relationships.

## Discussion

Our study explored nonverbal emotional expressions through participant drawings. Findings reveal alignment with previous studies;<sup>[3-6,11]</sup> red was most common for anger (57.43%), black for fear (38.14%), gray and blue for

**Table 1: Demographics of participants**

	<i>n</i> (%)
Age, mean±SD (range)	20.17±1.04 (19–25)
Gender	
Male	134 (63.2)
Female	78 (36.8)
Faculty	
Sport science	171 (80.66)
Public health and nursing	37 (17.45)
Others	4 (1.89)

SD: Standard deviation

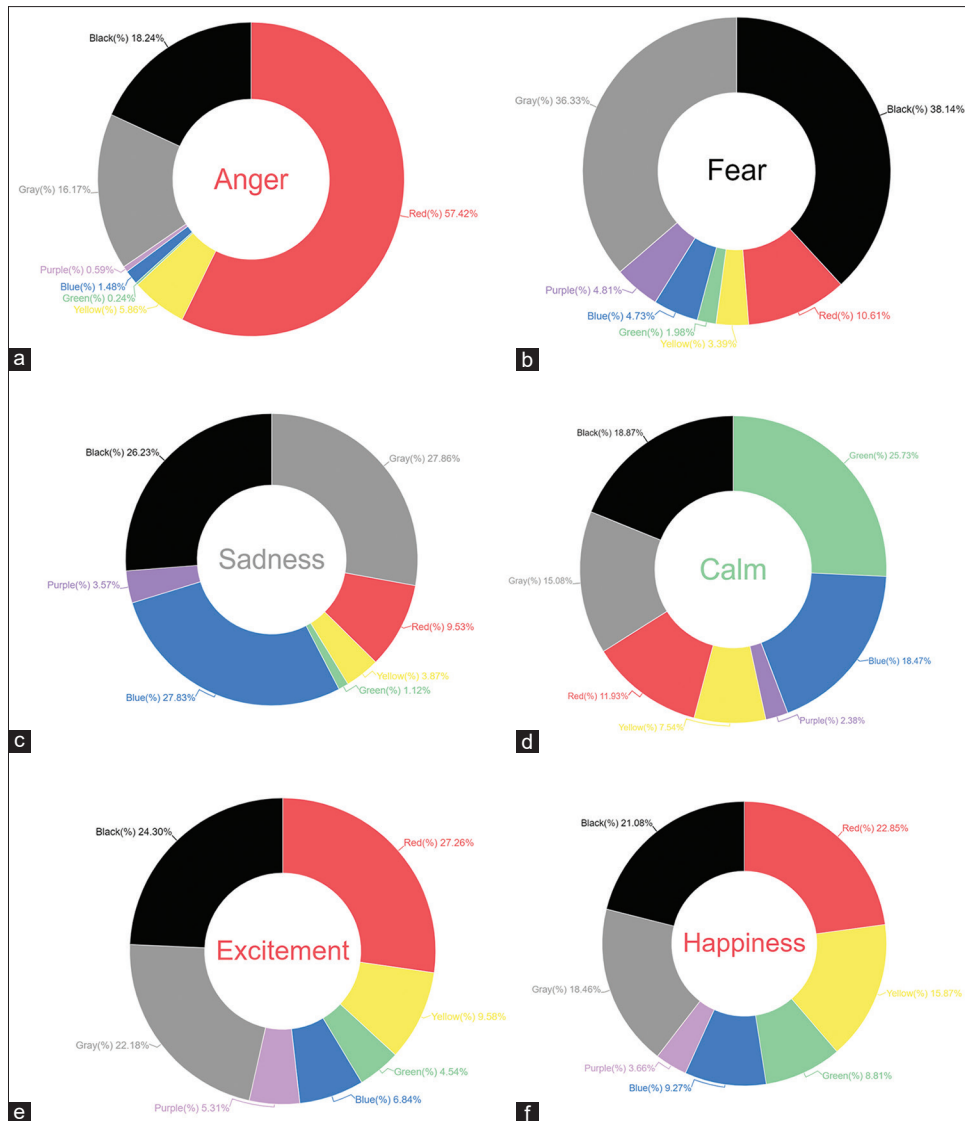


Figure 2: Prominent colors used by six emotions (n = 212). (a) Anger, (b) Fear, (c) Sadness, (d) Calm, (e) Excitement, (f) Happiness

Table 2: Comparisons of colors used, saturation, and brightness by six emotions

	Anger, mean±SD	Fear, mean±SD	Sadness, mean±SD	Calm, mean±SD	Excitement, mean±SD	Happiness, mean±SD	F	P
Color percentage								
Red	57.43±40.3	10.61±25.25	9.53±25.14	11.93±21.57	27.26±36.02	22.85±33.13	73.21	<0.001
Yellow	5.86±13.79	3.39±14.03	3.87±14.74	7.54±16.7	9.58±20.77	15.87±28.74	12.64	<0.001
Green	0.24±2.14	1.98±11.94	1.12±6.9	25.73±34.01	4.54±14.13	8.81±21.23	58.92	<0.001
Blue	1.48±8.67	4.73±17.4	27.83±39.27	18.47±30.78	6.84±19.24	9.27±22.27	33.16	<0.001
Purple	0.59±6.7	4.81±18.37	3.57±16.08	2.38±12.93	5.31±17.57	3.66±15.2	2.77	0.017
Gray	16.17±25.13	36.33±30.99	27.86±31.09	15.08±23.56	22.18±27.92	18.46±25.36	18.43	<0.001
Black	18.24±26.41	38.14±30.8	26.23±31.86	18.87±27.86	24.3±28.08	21.08±28.01	13.66	<0.001
Color number	2.61±1.37	2.8±1.36	2.85±1.55	3.42±1.65	3.18±1.7	3.48±1.87	10.47	<0.001
Color filled percent (%)	24.95±23.39	31.58±28	27.61±28.52	29.27±28.3	25.32±22.57	25.92±23.82	2.10	0.06
Image coverage percent (%)	73.38±19.47	77.14±19.43	74.16±21.06	79.61±20.53	79.07±15.94	76.43±19.31	3.59	0.003

SD: Standard deviation

sadness (27.86%, 27.83%), green for calm (25.73%), red for excitement (27.26%) and happiness (22.85%). Tangible styles dominated at 88-96%, with abstract styles peaking

for fear (12%) and lowest for happiness (3.8%). Emotion significantly influences color choices ( $P < 0.001$ ), color number ( $P < 0.001$ ), and image coverage ( $P = 0.003$ ).

**Table 3: Types of emotional depictions for six emotions (n=212)**

Style	Anger, n (%)	Fear, n (%)	Sadness, n (%)	Calm, n (%)	Excitement, n (%)	Happiness, n (%)	P
Tangible	191 (90.0)	187 (88.0)	195 (92.0)	196 (92.4)	193 (91.0)	204 (96.2)	0.07
Abstract	21 (9.9)	25 (12.0)	17 (8.0)	16 (7.6)	19 (9.0)	8 (3.8)	

Hypothesis 1 was supported. Mental health slightly affects the use of red ( $P = 0.015$ ), gray ( $P = 0.034$ ), and color fill percentage ( $P = 0.008$ ). Hypothesis 2 was partially supported. No significant moderating effects of mental health on the relationship between color and drawing style were found; thus, Hypothesis 3 was not supported.

Echoing previous studies,<sup>[3-6,9,11]</sup> our study has similar findings: participants predominantly chose red for anger (57.43%), black for fear (38.14%), gray and blue for sadness (27.86%, 27.83%), green for calm (25.73%), and red for both excitement (27.26%) and happiness (22.85%). Color choice is linked to emotional arousal and valence.<sup>[8,25]</sup> For instance, red is associated with high arousal and negative valence, often reflecting intense anger. Black used in fear-themed drawings indicates moderate arousal and negative valence, mirroring the uncertainty and anxiety associated with fear. Conversely, green in calm-themed images typically suggests low arousal and positive valence.

Our findings reveal that tangible styles were predominantly used, ranging from 88% to 96%, while abstract styles peaked at 12% for fear and dropped to 3.8% for happiness. This suggests a significant trend in emotional expression through drawing styles, aligning with approach and avoidance theory,<sup>[12]</sup> which posits that emotions influence behaviors either toward approaching positive outcomes or avoiding negative ones. Interestingly, abstract representations, particularly for fear, align with<sup>[26]</sup> Dael *et al.*'s observation that fear is often expressed subtly and is open to personal interpretation. Furthermore, the vigilance-avoidance pattern<sup>[27]</sup> in individuals with social anxiety may explain the preference for abstract styles in depicting fear, reflecting an internalized process of fear management where participants choose less direct forms of expression to avoid confronting or revealing their fears openly.

In our study, we observed a modest influence of mental health on color choices, with notable changes in the use of red, gray, and color-filled percentages. However, mental health had no significant moderating effect on the established relationships between color and drawing style. This outcome aligns with existing literature.<sup>[1-3,6]</sup> For example, these studies show common associations across different contexts, like yellow with joy and blue with sadness. Our results suggest that while mental health can influence individual color preferences, it does not significantly disrupt the broader, universal patterns of color-emotion relationships. This underlines the robustness of color associations across different mental health states, indicating that fundamental emotional responses to color

remain stable despite individual variations in mental health.

### Study implications and limitations

The study implications are as follows: first, our drawing-based approach innovates color-emotion research by allowing participants to create their images with a free choice of colors and content, moving beyond predefined color ranges. Second, our research identified minimal differences in mental health effects on emotional expression, though these moderating effects were not significant, adding to findings on minimal cultural and age-related effects on emotion-color associations.<sup>[6]</sup> Third, using Python and OpenCV, we transformed qualitative images into quantitative data, providing a more objective analysis of emotional representations compared to traditional subjective assessments.

The study's limitations are as follows: first, the homogeneity of our sample, comprised entirely of university students, restricts the broader applicability of our findings but enables a detailed examination of their emotional and color perceptions. Despite this, our results corroborate previous research indicating that emotion-color associations are generally universal, with only minimal differences due to culture and age, suggesting a minimal impact from sampling bias. Secondly, the type of device used for drawing, such as iPads versus smartphones, affects the detail of the images produced. When analyzing the content, the choice of device should be considered as it influences the outcomes. Third, our analysis was limited to 7 colors, grouping shades like pink, orange, or brown under broader categories like red. Developing the program to include a 12-color system could provide better insights and capture more nuanced emotional expressions.

### Conclusion

In conclusion, our study enriches color-emotion research by allowing participants to choose their colors freely, surpassing traditional limits. Although the effects of mental health on emotional expression were minimal, these findings add to the evidence of consistent emotion-color associations across cultures and age groups. Additionally, converting qualitative images into quantitative data using Python and OpenCV has significantly enhanced the objectivity of our analyses, advancing the field substantially.

## Authors' contributions

Hui-Ching Weng: Conceptualization, Methodology, Data curation, Writing- Original draft preparation, Visualization, Validation, Writing- Reviewing and Editing, Project Administration. Tanida Julvanichpong, Patchana Jaide, Kanchana Piboon, Puangtong Inchai: Methodology, Data curation, Validation, Formal analysis Longchar Imcha: Methodology, Data curation, Software, Validation, Formal analysis, Writing- Reviewing Liang-Yun Huang: Conceptualization, Methodology, Reviewing and Editing Pi-Chun Huang: Methodology, Software, Validation, Formal analysis, Writing- Reviewing.

## Data availability statement

This data has been coded and permanently de-identified. All data were accessible via the following web link: <https://osf.io/cv3hd/>.

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## Conflicts of interest

There are no conflicts of interest.

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