Colours of the Music: Towards Developing a Music-based Colour Palette through Associative Pairings for Home Lighting Systems

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ABSTRACT
This research focuses on gathering user-generated colour preferences based on different moods of music and exploring any cultural influences. The mood of music was determined by using energy and valence scores from the Spotify API. In Study 1, participants provided music-to-colour pairings for multiple music excerpts of varying moods. Study 2 had participants evaluate how well different music-based colour palettes represented the music based on the mappings from the prior study. The results of Study 1 indicated a correlation between music mood and colour choice, in addition to a preference for warmer, saturated colours for *happier* moods, and cooler, desaturated colours for *sadder* moods, except for the *intense* mood. The data did not provide evidence of a correlation between music-to-colour pairing and culture. The results of Study 2 revealed participants preferred user-generated colours from Study 1 the most, followed by colours created using an analogous colour palette scheme. These findings hold considerable implications regarding the design of a music-based colour palette for home lighting systems, demonstrates the potential of using valence and energy audio features from the Spotify API, and provides an initial set of user-generated music-to-colour mappings for future research.

Author Keywords
Music-based colour palette; home lighting systems; colour perception; music mood classification; Spotify audio features.

ACM Classification Keywords
• Human-centered computing → Human computer interaction (HCI) → Empirical studies in HCI → Designing interactive lighting.

MSc Contribution Type
Empirical.

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1. INTRODUCTION
As they become smaller and more efficient, light emitting diodes (LEDs) used in lighting systems are growing more popular in smart home setups since they can be positioned and embedded into many different environments. These lighting systems also have the capability for individually controlled parameters, such as intensity, saturation, and colour that change the experience of a space, bringing new functionality and forms of expression, through the use of light [36].

In the home environment, which is the focus of this thesis, the use of colour by LED-based lighting systems can play an important role, particularly in the space where people spend their social time [58]. While lighting has mainly focused on brightening spaces to improve visibility, with its greater control and adaptability the role of lighting has diversified [28]. Lighting does more than illuminate our surroundings. Lighting systems can enhance the visual aesthetics of a room to communicate contextual information and create a controllable atmosphere that can induce positive effects psychologically and physiologically [11,63]. Over time it will not be unusual for a large number of light sources to accumulate and seamlessly blend, becoming an interface for us to interact with. Typically, our interaction with these lighting systems is through an embedded controller system [25,38] using an Internet connected hand or voice device, such as a smartphone [37] or voice assistant.

As lighting systems are more likely to grow in their flexibility, it is important to consider how they can be designed for a more personalised experience and to generate desirable light effects in different contexts [43]. This is challenging since, especially in the home, people interweave different activities throughout the day and technology is expected to adapt accordingly. This requires a careful balance between overall system control and automation, to match different activities.

As such, an area for research in regard to home lighting is investigating how users coalesce their lighting systems with entertainment activities in their home. Lighting systems are capable of emitting different colours and dynamic light effects to seamlessly synchronise with activities, such as watching video content, playing video games [30], and listening to music [19]. As video entertainment is visually based, the coalescence of light effects, such as colour, is straightforward. On the other hand, music is a different modality. It is not visual. It is an abstract art form, which people interpret differently. This subjective response is affected by cultural background, musical preference, musicality, current mood and many other factors.

As demand for lighting systems grows, dedicated apps to facilitate the use of light effects when listening to music have emerged. These apps use a smartphone's microphone in combination with metadata of the music in order to produce colour and dynamic light effects that synchronise to the beat of a song. This demonstrates that lighting effects (dynamics and brightness) can be successfully controlled to interact with music algorithmically, by understanding the different sections of a song. However, this does not pertain to hue or colour. While there is a systematic algorithm for selecting colour choices for lighting systems when watching video or playing games, there is currently no evidence indicating how the colour choices are being selected in relation to the music being played.

Current Study

This current study is relational research that aims to investigate techniques in developing a user-generated music-based colour palette through associate pairings of music to colour. Since a colour palette implies a range of colours, this research takes a two-stage approach. The present research tackles the problem by conducting two online studies to (1) gather user-generated music-to-colour preferences based on music of different moods and exploring how culture might influence these preferences; (2) evaluate how well user-generated and generative colour palettes represents the mood of a piece of music.

This thesis is structured as follows: An in-depth literature review that introduces the status quo and current challenges of music-to-colour mappings. This is followed by the methodology and results of the main study in gathering user-generated music-to-colour preferences. The methodology and results of the second study are then reported in evaluating how well the colour palettes serve in representing the music. A subsequent discussion recapping the research questions and interpreting the findings regarding both studies is then reported. Finally, a conclusion briefly reviews the main findings of this research, its limitations and recommendations for future research.

2. RELATED WORK

This section lays out the theoretical foundation for the empirical research on music-to-colour associative pairings in the context of home lighting systems. The structure of this literature review will be as follows: (1) Past and existing music-to-colour mappings; (2) The role of emotion and mood for both music and colour; (3) Home lighting systems and music in context; (4) Measuring the energy and valence of music; (5) Cultural factors involved with colour preferences.

Mapping Music to Colour

Humans have been interested in the relationship between music and colour for centuries. In fact, it is well reported how the earliest attempt of mapping music to colour dates back as early as Isaac Newton when he discovered how white light could be divided into spectral colours [53], naming them: red, orange, yellow, green, blue, indigo, and violet, or ROYGBIV for short. The colours were represented into a colour wheel, which serves many purposes today. Newton decided to name the seven ROYGBIV colours simply because he took to the idea that colours of the rainbow should be analogous to the seven steps of a diatonic scale [16]. While this was a purely aesthetic choice, this was not the only time that harmonic relationships in music were used as a mapping to colour.

In the 1980s, Wells [68] extended Newton's idea of using the musical scale as a technique for music-to-colour mappings by mapping pitch classes to 12 hues of colour based on equal spacing of the 12 half steps in a Western musical scale, and even identified how halving both could reduce the number of colours mapped to the 6 steps of a whole tone scale. Well's findings, however, were through a proposed correlation rather than gathering empirical evidence. Similarly, researchers Mardirossian and Chew [39] used the key of the music as a way to assign colour for specific music visualisations, so that each key had a separate colour.

When visualising concurrent tones and melodies using colour, Ciuha et al. [8] found that taking low-level features of the audio sample could affect the resulting colours. These music features included the sound's frequency, beats per minute and loudness of the tones, such as dynamics. This novel method to visualise music used music features to good effect. With the inclusion of these music features, it resulted in the situation where similar tones, chords, and keys would have similar colours to each other, visualising their harmonic relationship. Furthermore, dissonance and consonance in the music were represented by lower and higher saturation.

Crucially, while these techniques of using colour to link to music are interesting, they primarily are in a music visualisation context rather than for home lighting and are designed with the focus of music production. Furthermore, colour mappings were not based on empirical evidence, but instead were assigned automatically to different theoretical aspects of music [e.g., 68, 39, 8]. In practice, this may differ from other forms of music-to-colour mapping found in home lighting systems.

Obtaining the most 'correct' colour for music is a challenging task, and some research has turned to the physical phenomenon of synaesthesia for music-to-colour mappings. Nevertheless, despite there being evidence of aesthetic appeal for auditory-visual mappings sourced by synaesthetes for people without synaesthesia [66,45], synaesthesia is difficult to research. Not only is it an incredibly rare condition but each synaesthete has a unique response to music stimuli, so it is impossible to generalise. As such, this thesis focused on music-to-colour mappings in non-synaesthetes only.

The Role of Emotion & Mood

Emotion is an important characteristic inherently shared between both colour and music. Many studies have identified there being a link between colour [59,61,31] and saturation [71] with emotion and mood. We have so many associations between colour and emotion that it is even possible to describe our emotions with colour, such as being "red with rage", "green with envy" or experiencing "the blues" [6]. Music is similar in this regard, and it is common to find Italian musical expression marks in classical music scores, such as *allegro*, *misterioso*, and *tranquillo* to mean happy, mysterious, and calmly respectively. Research into music and emotion has attributed this link to both a combination of psychophysical cues [57,29], such as timbre or tempo, and culture-specific cues [2,21,20], such as through expert cultural experience or exposure.

Given its clear link, a great deal of research has used mood and emotion as a mediating factor in music-to-colour mappings. Using a song's mode, either major or minor, has been employed to investigate music to colour correspondences. Sebba [54] reported how her musical students would associate major music with warmer, more saturated colours than minor music. Similarly, Bresin [5] found that music in the major mode were associated with lighter colours, while songs in a minor mode were darker. While the mode can certainly denote the mood of a piece, it is only one of many high-level features to describe the emotion of music.

Barbiere et al. [4] had participants listen to four different songs, determine what emotion the song was, as either "happy" or "sad", and rate how well 11 individual colours elicited the emotion they determined the song to be. Notably these were for the names of colours, and not visual representations of the colour themselves. The results indicated that brighter colours (yellow, red, green and blue) were more commonly assigned to happier songs, while grey was more commonly assigned to songs determined as "sad". Importantly, only four songs were used against two very broad emotions. Moreover, assigning a colour to an entire song is a difficult task since songs can easily fluctuate between different emotions.

Holm et al. [23] investigated music-to-colour association using genre, by asking participants to select 12 colour patches and their associated genre word label. The results suggested there was an association of Rock with black, Blues with blue, and Pop with pink, but the reason for the selection of the audio-visual categories has been critiqued as arbitrary [35]. While an intuitive approach, using genre to gather music-to-colour mappings is problematic since genre is not inherently innate to music. That is, genre is not a physical property in the sound and does not contribute to its psychoacoustics [56]. Therefore, using genre to measure the specificity of musical emotions is fundamentally vague, since genre is a cognitive and cultural construct, with no clear boundaries or taxonomy [3].

A study in 2011 by Palmer et al. [44] found that faster music could be associated with more saturated and lighter colours, while slower music was associated with the opposite. In a follow-up 2013 study, Palmer et al. [45] proposed the emotional mediation hypothesis, which posits that colour and music are linked through shared emotional associations. The study was conducted by using participants from the US and Mexico to select colours from a 37-colour array that they found the most and the least consistent to 18 different 50 second samples of classical music that varied in tempo and mode. They found that for both culture groups, music in the major mode and higher tempo would produce colour preferences that were more saturated, lighter, and more yellow. Conversely, music in the minor mode and with a slower tempo, would produce desaturated, darker and bluer colours. These results have been replicated using similar classical pieces [26] and also using different genres of music [56].

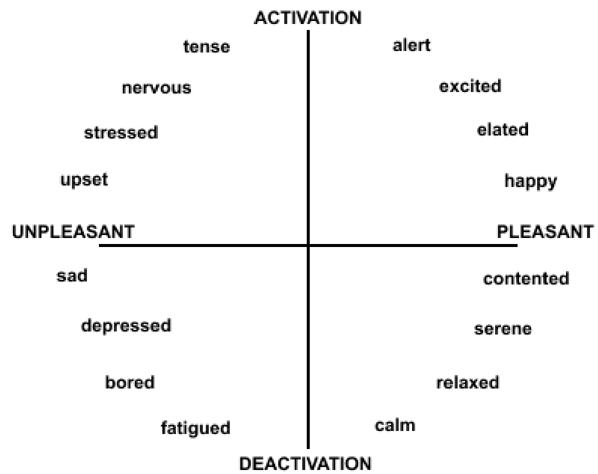

Figure 1. The circumplex model of emotion [47]. In this study, the horizontal axis represents valence and the vertical axis represents energy.

An alternative way of quantifying the level of emotion, other than only if the piece is major or minor is by connecting aspects of music to Russell's circumplex model of emotion [52]. This originally used factor-analytic evidence to spatially map different affective concepts into a circle (see Figure 1), going through the emotions of pleasure, calmness, sadness and stress [47]. Since then, the circumplex model has been used as a method to analyse and classify the emotional qualities of a piece of music in music-to-colour studies [e.g., 56,46,35,14,42]. Moreover, after replicating Palmer's 2016 study, Whiteford et al. [70] concluded that the two affective factors arousal (i.e., energy) and valence are most effective in predicting colour to appearance dimensions in music-to-colour associations, in addition to showing robust evidence of the emotional mediation hypothesis.

Researchers Dharmapriya et al. [14] used Russell's Circumplex Emotional model in the context of categorising songs based on their valence and arousal (i.e., energy) and then applied an Itten colour wheel behind it for its colour mappings. Conducting feature extraction and audio analysis to get valence-energy scores per song, they mapped the valence-energy scores to a position on the colour wheel in order to get colours. They then compared multiple classification methods to calculate valence-energy scores, such as Random Forest, and concluded that Russell's Circumplex model could be an effective way to synchronise music to colours. That said, it needs to be questioned how their audio analysis might differ from Spotify's and what their justifications were for applying Itten's colour system the way they did.

Home Lighting Systems & Music

The perception of a space's atmosphere will be significantly affected by both the dynamics of the lighting and the colour ranges used [34]. Similarly, many studies have suggested how the use of specific colours can influence our mood. For example, the use of cool colours, such as blue and green, have a relaxing effect while colours with a long wavelength, such as orange and red, are stimulating and even protective [69,64]. The challenge however is that this can shift between different contexts and situations. In particular the emotional perception of colour can vary depending on the user's context. Listeners can switch between perceived and induced musical emotions [46], which can be difficult to control for. Moreover, evidence suggests that people who are exposed to LED lighting with colours whose saturations are enhanced, will have a higher preference for that colour [18]. Explanation for this is that the observers' preferences for the appearance of a colour corresponds to the mental models they have for colour vividness. Effectively, increasing the colour saturation in LED lighting may yield better visual clarity and an enhanced perceived brightness [18]. Moreover, more saturated LED light can lead to people feeling less tense, cosier, safer, and also livelier in atmosphere perception [65].

When exploring the effects of context on home lighting systems, researchers Jung et al. [28] identified two contextual factors that could influence how either a user or system could manipulate lighting parameters: (1) levels of concentration required; (2) social interaction. Through an in-person experiment, they found that listening to music required a low level of concentration but was mostly a social experience. Their results suggested lighting parameters such as illuminance, colour temperature, and hue significantly depend on how much people need to concentrate. By contrast, other home activities such as watching TV or gaming were found to be both low social interaction but required high levels of concentration. They concluded the degree of concentration is a large factor required for 'pleasant' lighting use and from this, there are common patterns people take in this regard despite personal differences in lighting preferences.

There are a number of smartphone applications, such as Chromania [7] and Hue Disco [24], that are able to connect and synchronise light effects, as well as colour, to music being played in the background using the device's microphone. Most notable of the apps, and the leading solution is iLightShow [1], which analyses music played in the background using metadata and audio features from the song's streaming service, such as Apple Music or Spotify. Using this data allows the app to use a sophisticated algorithm that knows in advance when to synchronise light effects to the beat of the song. Although, this algorithm is not perfect. Upon testing, the colour palette repeats the same colours throughout. Users have control over properties of the light, such as brightness, intensity and saturation, however how the colour are decided appears to be random in relation to the music. Ensuring what colours are appropriate for a given piece of music is a challenging task, because of its inherent cross-modality. Even by using song metadata, current solutions seem to struggle and colour mappings have no correlation to the music and selects seemingly random colours. As a result, colour choices are not consistent on repeated playback, and colour mappings are different when a song is repeated.

Research by Moon et al. [41] have focused on obtaining music-to-colour preferences, specifically in the context of lighting systems. In their initial study, they had participants listen to multiple 12 second segments of a song and then list mood and colour preferences for the song. They concluded that the emotions elicited when listening to music can be enhanced by matching the colour of the ambient illumination to the mood of the music playing. However, this should be considering the listener's own personal preferences. A follow up study by Moon et al. [42] focused on developing a custom lighting system that automatically detects the mood of song and expresses the mood through synchronised lighting effects and colour changes. By analysing the indirect associations between mood words and colours through a web questionnaire on over 200 participants, their data analysis generated lighting scenarios that could reflect changes in the mood of the music. Notably, the researchers conducted their own mood analysis on the music using MIRToolbox to extract music features such as timbre, tonality, rhythm, and song structure [33]. While the best performing mood classification scored an accuracy score of <70%, by their own admission the mood classification model needed improvement [41].

Measuring Mood in Music

As discussed in the Mapping Music to Colour section, music theory is not the most accurate way to capture the mood of a song. For example, the view that a piece written in a major key would mean it fits to a positive mood, is false. Nor is the key to a song relevant, since songs can modulate in key and be transposed. Song genre is too imprecise, as songs can be of multiple genres. When looking to map music to colours, mood has been used as a shared characteristic.

An interesting avenue for investigation is utilising existing computational analysis models of mood within music [27], which has been part of the secret to success for recommending new music on online music streamers, such as Spotify.

The Spotify API [67] provides artist, album, and song data alongside two endpoints to retrieve content-based music information: Audio Analysis and Audio Features. Audio Features is focused on characterising and comparing different songs, while Audio Analysis is used more for content-based information retrieval. These music listening tools have originated from Jehan's PhD thesis [27], which describes in detail how each of the extraction methods work. His approach presented the idea of segmenting audio features based on onset-detection, rather than sampling features based on a regular interval. This onset-detection is based on identifying abrupt loudness and sudden variations in pitch or timbre. This has the goal of segmenting the music so that each section has consistent properties across its duration. This allows for more musically dense parts of a song being segmented in more detail than a slowly moving part of a song.

Out of the 12 audio features available for each track, this thesis will focus on the perceptual measures of a track's energy and valence, since emotion is a strong shared characteristic between music and colour. Energy represents the song's intensity and activity, and is a score between 0.0 to 1.0, with scores closer to 1 being energetic and noisy. Meanwhile, valence describes the musical positiveness the track conveys. Tracks with a higher valence between 0.0 to 1.0 will have a high valence that sounds more positive, while tracks with low valence will sound more negative.

The Audio Analysis endpoint allows us to explore the audio information for sections of a song. Sections within the Spotify API are markers that define a portion of the song with large variation in rhythm or timbre, such as a song's chorus, bridge section or even guitar solo. Within each section contains descriptions of tempo, key, mode, time signature as well as loudness [67]. An advantage of choosing Spotify Audio features for this study is its inherent availability. Apart from the convenience, Spotify has the resources to develop algorithms for in-depth audio analysis well beyond the scope of this study.

Cultural Dimensions

A relevant cultural dimension that can help explain cultural differences between music-to-colour mappings is the concept of individualism. Originally, the concept of individualism was created by Hofstede through research with IBM [22] and is an index to measure cross-cultural hypotheses [50]. The individualism vs collectivism (IND-COL) spectrum refers to the "degree to which individuals are integrated into groups" [22]. Individualistic cultures will have people who tend to look after themselves and their immediate family, meanwhile collectivistic cultures will be people in strong, cohesive groups, often extended families, who continue to protect each other for unquestioning loyalty. The IND-COL spectrum can be divided into four dimensions that takes into account, horizontal and vertical cultures. Table 1 describes the four different dimensions.

Horizontal Individualist	People view themselves as equal to others in status and the focus is on expressing one's uniqueness and self-reliance. E.g., New Zealand, Sweden, Denmark.
Vertical Individualist	People tend to be concerned with improving individual status and distinguishing themselves from the competition. E.g., U.S., France, Great Britain.
Horizontal Collectivist	People focus on sociability and interdependence with others in an egalitarian context. E.g., rural communities in Central America, the Israeli Kibbutz.
Vertical Collectivist	They emphasise the integrity of the in-group, are willing to sacrifice personal goals for the sake of the whole. E.g., Japan, India, China.

Table 1. Horizontal and vertical individualism and collectivism [55].

These cultural leanings can influence colour preferences. Colour can have a series of meanings and interpretations to various people from different regions of the world. For example, the colour orange may be viewed as a positive, warm, spiritually enlightened colour in Asia, however in the United States, it is a colour of road hazards, construction works, and fast food [12]. As posited by multiple researchers [e.g., 45,35,70], both music-to-colour mappings and our perception of colour can be influenced by our own personal preferences, however, data from prior studies is unclear on the evidence whether it can be culturally shaped. In the study by Palmer et al. [45], when the same experiment, which was originally conducted in the United States, was replicated in Mexico, there was a high correlation for colour mappings between cultures, indicating no effects of culture on colour-to-music associations. Instead, they found more energetic music produced colour choices that were more saturated, lighter and yellower while sadder music produced the opposite pattern. The data between the two cultures was almost identical and shows some generalisation across cultures is expected, however the strength of generalisation is unclear since people from Mexico still have extensive exposure to Western music and culture [70].

On the other hand, despite one of the leading studies in music-to-colour mappings suggesting no difference in culture, the perception of music without colour associations has been shown to be influenced by an individual's cultural lens. In a study by Demorest et al. [13], listeners of music from different cultures were able to recall music that was within their own culture, regardless of context. However, it must be stressed that this study was not specific to music-to-colour mappings.

There are many different factors such as current mood, age, musical preferences and gender that may influence people's perception of emotions, colour and music [46]. While the delineation of musical emotions is unclear, and by no means universal for all, an explanation is perhaps due to cultural generality of associations between emotion and colour [70]. This essentially posits that because there is generally a fair agreement of semantic dimensions such as valence or arousal across cultures, there is a possibility that music-to-colour mappings have some degree of cultural influence.

3. RESEARCH QUESTIONS

Based on the reviewed literature, there have been several attempts and different approaches toward mapping music-to-colour. In particular, the use of mood and emotion as a shared characteristic for research is a highly promising method, which can be captured using data sourced from the Spotify API. However, very few studies focus on developing colour mappings for lighting systems. Moreover, existing music-based colour palettes are lacking user-generated evidence to support which colour mappings are appropriate in relation to the mood of the music.

In an effort to better understand the contribution of mood within music in regard to music-to-colour mapping associations, the following research questions were constructed:

RQ1. What patterns exist between the mood of the music and the music-to-colour mappings which people have? What recommendations can be made in creating a music-based colour palette for home lighting systems?

RQ2. Are there any cultural factors that could influence the music-to-colour mappings people choose based on the mood of the music?

RQ3. What colour harmony rules can be used in order to procedurally increase the number of music-to-colour mappings in the context of home lighting systems with multiple light sources?

4. STUDY 1: MUSIC-TO-COLOUR MAPPINGS

The overall purpose of this study was to collect music-to-colour mappings so that the link between the mood of a song, divided by music category, and colour preferences could be investigated. Furthermore, the study also aimed to investigate any influences on colour preference based on cultural background, divided by IND-COL group.

4.1 Method

Participants

Participants for this online study were recruited using the Prolific platform [48]. They received a reward of £3.15, which corresponded to approximately £7.51 per hour. The study took approximately 25 minutes to complete. The filter criteria that were applied included having a proficiency in English, no form of hearing difficulties, and normal or corrected-to-normal vision, meaning that they were able to see colour normally. After data collection, four of the $N = 54$ participants were excluded, as they were suspected of disregarding the task's instructions since they failed the colour choice attention checks. These attention checks flag and removes submissions that are deemed to be too random, in which they selected colours on opposite sides of the colour wheel for the same song more than three times. The remaining $N = 50$ participants were an average $M = 25.36$ ($SD = 8.66$) years old, and $n = 36$ (72%) were female ($n = 14$ were male).

Materials

This study used a Qualtrics survey to conduct both capturing cultural dimensions of the participant and colour preferences in a music-to-colour mapping task. To collect the data for this study, selecting songs and colours that would be suitable had to be pre-processed. The following subsections describe the process of identifying and obtaining songs used for this study through the Spotify API, the colours that participants could select their music-colour association to, and the UI used for the online questionnaire in order to obtain mappings.

Cat.	**Mood**	**Valence-energy levels**	**Logic range**
1	Excited	*High* valence & *high* energy	valence ≤ energy
2	Happy	*High* valence & *high* energy	*valence > energy*
3	Serene	*High* valence & *low* energy	*valence ≥ energy*
4	Calm	*High* valence & *low* energy	*valence < energy*
5	Depressed	*Low* valence & *low* energy	*valence* ≤ energy
6	Sad	*Low* valence & *low* energy	*valence > energy*
7	Upset	*Low* valence & *high* energy	*valence ≥ energy*
8	Intense	*Low* valence & *high* energy	*valence < energy*

Figure 2. Music categories with the moods associated [47] to a set valence-energy level.

Dataset & Song Selection

The stimulus used in this study was exposing participants to different song excerpts varying in different energy-valence levels. Data about songs were scraped using the Spotify Web API and Spotipy [32], the latter being a lightweight Python library to more easily interact with the API. Songs were selected by scraping the metadata and audio features of each track in five playlists, found using the Spotify app. Taking into account possible influences such as music preference and popularity, careful judgement was carried out on sourcing songs from each playlist. Nonetheless, songs were ultimately chosen based on their energy and valence scores. These songs were then filtered according to their energy and valence scores and sorted into their relevant mood category. The logic ranges, associated moods, and energy and valence scores can be seen in Figure 2. A list of the selected songs can be found in Appendix 1 and furthermore, how they fit within each mood category, in terms of energy-valence, can be visualised in the scatter plot in Figure 3.

Initially, the dataset of song excerpts was 40 songs. This was reduced, however, after a pilot test on five participants revealed the study took over 30 minutes to complete. Due to budget constraints, these costs would be prohibitive and therefore the overall time to conduct needed to be reduced. The dataset was reduced to 3 songs per category.

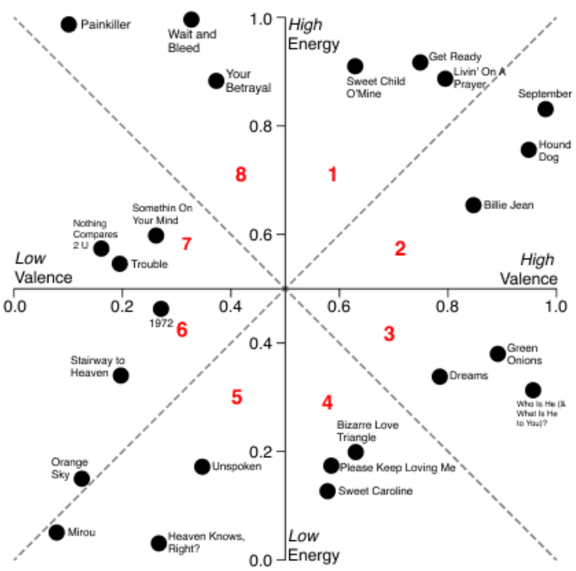

Figure 3. Scatter plot showing songs used in the dataset.

Colour Choices

The colours available for the music-to-colour mapping task were based on the colour swatches from the Berkley Colour Project 37 (BCP-37) used in the study by Palmer et al. [45]. The BCP-37 comprises 37 different colours and contains 8 main hues of red, orange, yellow, chartreuse, cyan, blue and purple at 4 different levels of saturation and lightness, which were originally systematically formulated using the Munsell Colour System. The remaining colours of the 37 included muted, dark, and achromatic cuts of the main hues.

Since LED lighting systems illuminate colours differently from other lighting sources, such as on a laptop screen, not all of the colours from the BCP-37 were appropriate for this study. While saturation in colour can be represented in an LED lighting system, and even have an influence on the visual clarity of a colour [18], colours that had muted, dark, and achromatic cuts would not be suitable. As a result, these cuts of colour were removed. Furthermore, LED lighting systems are able to illuminate the colours magenta, indigo and cyan. Since humans are trichromatic [15], these colours are visible to them, can be seen at different saturations levels and therefore added to the list of colour choices.

The final list of colour choices the user was able to select from in the music-to-colour mapping task comprises of 20 colours, consisting of 10 different hues, each with a desaturated and saturated cut. The list of colour choices with HEX code values can be seen in Appendix 2.

Measuring Cultural Dimensions

In order to accurately measure cultural dimensions, a modified version of the individualism and collectivism scale was used as part of a questionnaire before the music-to-colour mapping task. This version, created by Triandis & Gelfand [60], is a shorter 16-item version designed specifically to capture individualism and collectivism at vertical and horizontal levels. The way it measures IND-COL is by presenting 16 statements for a participant to answer on a 9-point Likert scale. This ranges from 1 = never or definitely no and 9 = always or definitely yes. The four statements each refer to a dimension of collectivism and individualism. The exact wording of each statement used in this study, can be found in Appendix 3.

Procedure

Details about the study were posted on Prolific and were only available to their participant pool who fit the defined filter criteria. Participants were required to conduct the study on a desktop or laptop device and use audio. After signing up through Prolific, appropriate participants received the hyperlink to the online Qualtrics survey and were required to read an information sheet about the goals of the study as well as giving informed consent. Participants were then instructed to adjust their browser window to be at least 990px wide by 440px tall. They were also given information with an overview of the structure of the study, which consisted of two sections: (1) a simple questionnaire about their cultural background and (2) an interactive music-to-colour mapping task.

The first section began by confirming details that were a part of the filter criteria on Prolific, such as their age and if they had any form of colour vision deficiency. They then completed the IND-COL scale questionnaire and were instructed to take the time to read each statement and rate how much they agreed with each statement on a scale of 1-9. Each IND-COL statement was programmed to appear in a random order.

Participants were then given an audio warning before they moved onto the music-to-colour mapping task. Specifically, they were instructed that, before they proceed to the next section, they adjust their volume settings, so it was at a comfortable setting and to ensure they were in a noise-free environment in order to hear song excerpts properly. As an added measure to ensure participants were exposed to the song excerpt and for speed reasons, the song excerpt would play automatically and looped when conducting the task. Participants were warned about this beforehand and were recommended to use headphones; however, this was not a requirement.

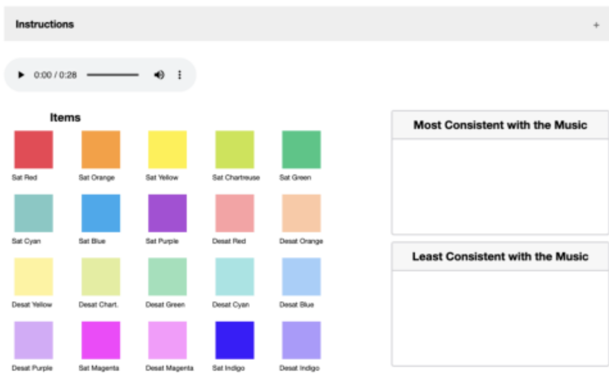

Figure 4. Screenshot of the user interface (UI) for the music-to-colour mapping task.

The music-to-colour mapping task consisted of participants being instructed to listen to the audio clip in full, as many times as needed to get a 'feel' for the music. Once they felt familiar with the song excerpt, they then had to drag and drop 3 colours into two groups that they thought were the most consistent and least consistent with the music. They then had to order their colour choices in the relevant group so that the top choice was either the most or least consistent with the music, the second, and third most or least consistent with the music. A snapshot of the UI used for this study is seen in Figure 4. Participants could not proceed onto the next question until they had selected 3 colours into each group, otherwise an error instructing them to finish the task would appear. Once they had dragged and dropped the colour into one group, they could not use the same colour twice. All participants repeated this task on all 20 songs in the dataset, including the four attention check questions.

Design

This study used a 4 x 8 factorial mixed design that combined features of a between-subject design, in order to factor in different IND-COL groups, as well as a within-subject design, in order to expose each participant to all different types of music mood.

The first independent variable was the mood of the music. Specifically, this was quantified by what *music category* the song excerpt fit into. The *music category* variable has 8 different levels (see Figure 2), which go through different ranges of valence-energy levels.

The second independent variable was the *IND-COL group* of the participant, comprising of 4 levels: *vertical individualist*, *horizontal individualist*, *vertical collectivist*, and *horizontal collectivist.* Whether or not the participant was a part of a specific IND-COL group depended on their score in the first part of the questionnaire (see Appendix 3).

Hypotheses

With the original research questions set out at the beginning of this thesis, this study is focused on mapping colours based on the music-to-colour task, as well as whether or not cultural factors were in play, so that the participant fit under a particular INDCOL group.

Given the previous related works, the following hypotheses were formulated for Study 1:

H1. When participants listen to song excerpts in mood categories 1 and 2, they would prefer warmer colours (e.g., red, orange, and yellow) and would prefer cooler colours (e.g., blue, green, and purple) when they listen to song excerpts in mood categories 5 and 6.

H2. There is a relationship that exists between the level of Individualism-collectivism and the colour preference they have between groups when they listen to songs of different categories and varying levels of valence and energy.

H3. When participants listen to song excerpts in mood categories 1 and 2, they would prefer more saturated colours, and would conversely prefer desaturated colours when they listen to song excerpts in mood categories 5 and 6.

H4. There is a relationship that exists between the level of Individualism-collectivism and the saturation levels of the colour preference they have between groups when they listen to songs of different categories and varying levels of valence and energy.

4.2 Results

The data analysis for this study and the proceeding study was performed using Python (v3.8.8) [49], utilising the libraries Pandas [40] and Pingouin [62]. Table 2 provides an overview of the means and standard deviations of the data. Table 3 gives an overview of the statistical results.

Power Analysis

An *a priori* power analysis was conducted using G*Power 3 [17] to determine the sample size required for a two-way ANOVA between two independent group means, with a large effect size ($d = 0.8$), and an alpha of 0.05. Results showed that a total sample of 43 participants was required to achieve a power of 0.8.

	Colour Choice		***Saturation***	
Variable	***M***	***SD***	***M***	***SD***
Mood Category				
1 (Excited)	10.09	6.24	1.16	0.37
2 (Happy)	9.08	6.39	1.20	0.40
3 (Serene)	9.97	5.66	1.50	0.50
4 (Calm)	10.03	5.37	1.70	0.46
5 (Depressed)	10.82	4.95	1.73	0.45

6 (Sad)	9.42	4.82	1.75	0.44
7 (Upset)	10.93	5.47	1.59	0.49
8 (Intense)	8.25	6.88	1.05	0.21
IND-COL				
Horizontal Individualists	10.01	5.74	1.16	0.49
Vertical Individualists	9.31	5.79	1.20	0.50
Horizontal Collectivists	9.99	5.91	1.50	0.50
Vertical Collectivists	9.64	5.68	1.70	0.50

Table 2. Overview (means and standard deviations) of colour choices for mood category and IND-COL.

H1: Colour Mappings & Mood Category

A factorial Analysis of Variance (ANOVA) was used to examine H1 which proposed that when participants listened to song excerpts in mood categories 1 and 2 (high valence & high energy) they would prefer warmer colours, while for mood categories 5 & 6 participants would prefer cooler colours. The independent variables represented the mood of each song excerpt, (categories 1 - 8) and the IND-COL group (horizontal individualism or collectivism, or vertical individualism or collectivism) the participants belonged to. The dependent variable was the 3 most consistent colour preferences that participants selected to go with the song excerpt. An overview of the means and standard deviations for each group can be seen in Table 2.

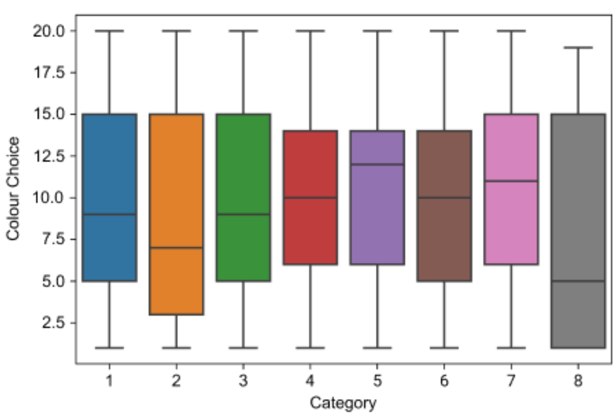

Figure 5. Box and whisker plots of the colour preferences for each mood category.

On inspection of the histograms of the data (see Appendix 4) and box and whisker plot, seen in Figure 5, the data is not normally distributed. To confirm this, a *Shapiro-Wilks* test was conducted, which indicated the data were not statistically normal ($p < 0.001$). The *Levene's F* test revealed that the homogeneity variance assumption was not met ($p < 0.001$). As such, the *Welch's F* test was conducted using mood category as an independent variable. The *Welch's* ANOVA on the mood category of the song on colour choice revealed a statistically significant main effect, $F(7,1383.66) = 8.99$, $p < 0.001$, indicating that the null hypothesis should be rejected and that the mood of the songs did have an effect on colour choice.

Post hoc comparisons were conducted using the *Games-Howell* procedure in order to determine which pairs of the 8 mood category means differed significantly. The results indicate 9 combinations of moods that were significant. These include a significant main effect in colour preference: when participants listened to the mood category 1 (M = 10.09, SD = 6.24) compared to mood category 8 (M = 8.25, SD = 6.88), with a positive effect size (g = 0.28); when participants listened to mood category 2 (M = 9.08, SD = 6.39) compared to mood category 5 (M = 10.82, SD = 4.95), with a negative effect size (g = -0.30); when participants listened to mood category 2 (M = 9.08, SD = 6.39) compared to mood category 7 (M = 10.93, SD = 5.47), with a negative affect size (g = -0.31); when participants listened to mood category 3 (M = 9.97, SD = 5.66) compared to mood category 8 (M = 8.25, SD = 6.88), with a positive effect size (g = 0.27); when participants listened to mood category 4 (M = 10.03, SD = 5.37) compared to mood category 8 (M = *8.25*, SD = 6.88), with a positive effect size (g = 0.29); when participants listened to mood category 5 (M = 10.82, SD = 4.95), compared to mood category 6 (M = 9.42, SD = 4.82), with a positive effect size (g = 0.29); when participants listened to mood category 5 (M = 10.82, SD = 4.95), compared to mood category 8 (M = 8.25, SD = 6.88), with a positive effect size (g = 0.43); when participants listened to mood category 6 (M = 9.42, SD = 4.82), compared to mood category 7 (M = 10.93, SD = 5.47), with a negative effect size (g = -0.29); when participants listened to mood category 7 (M = 10.93, SD = 5.47), compared to mood category 8 (M = 8.25, SD = 6.88), with a positive effect size (g = 0.43). The full results of the post hoc test, with exact significance values are provided in Table 1 within Appendix 5.

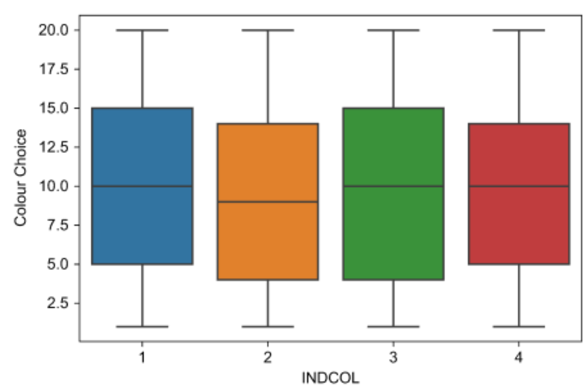

Figure 6. Box and whisker plots of colour preferences IND-COL group.

H2: Colour Mappings & IND-COL Group

H2 proposed that depending on what type of cultural background a participant had, there would be a relationship that exists between the IND-COL score and the colour preference they would have when they listened to song excerpts of varying mood categories. Similar to the statistical analysis of H1, the homogeneity of variances assumption was not met from a *Levene's F* test that was conducted. As a result, to test this hypothesis, the independent variable used was the IND-COL group the participant classified themselves as, while the dependent variable were the colour preferences they had selected to be most consistent with the song excerpt. The overview of the means and standard deviations for each group is seen in Table 2 and distribution of colour choices between IND-COL groups in Figure 6. A more detailed view of the distribution can be seen in a histogram on Appendix 4.

Since the homogeneity of variances assumption was not met, a *Welch's* ANOVA was conducted. This revealed that IND-COL group did not have statistically significant main effect, $F(3,1440.37) = 2.32$, $p = 0.074$. This result indicates the data in this study provided little evidence that the null hypothesis is false. Therefore, the null hypothesis should not be rejected, and the data indicates cultural background of the participant did not have an effect on colour preference. As a result, a post hoc comparison test was not conducted.

Effect	***df1***	***df2***	***F***	***p***
Colour Choice (H1 & H3)				
Mood Category	7	1383.669	8.991	0.001*
IND-COL	3	1440.371	2.320	0.074
Saturation (H2 & H4)				
Mood Category	7	1368.290	278.55	0.001*
IND-COL	3	1429.610	2.848	0.036*

** significant*

Table 3. Results of Welch's ANOVA performed on Colour Choice and Saturation.

H3: Saturation & Song Category

H3 proposed that when participants heard song excerpts from mood categories 1 and 2, which were both high valence and high energy, participants would select colours that were saturated. Conversely, when participants heard song excerpts in categories 5 and 6, with low valence and low energy, then participants would select colours that were desaturated. Colour preference responses were pre-processed to determine whether the response was of a saturated or desaturated colour. An overview of the means and standard deviations for each group can be seen in Table 2. The proportions of saturated or desaturated colour preferences are visualised in Figure 7.

A *Welch's* ANOVA was used to analyse this hypothesis, with the independent variable being represented by the mood of the song excerpt and the dependent variable the colour preference they selected. The results of the ANOVA revealed a statistically significant main effect, $F(7,1368.29) = 278.55$, $p < 0.001$, indicating that the null hypothesis should be rejected and that the mood of the songs did have an effect on whether participants preferred saturated or desaturated colours.

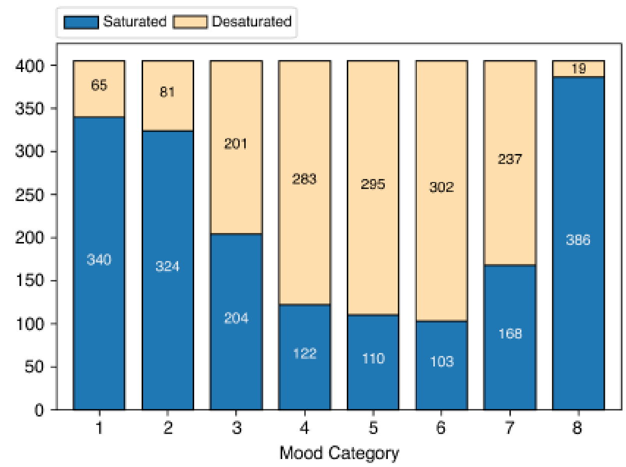

Figure 7. Stacked bar chart showing the proportion of saturated colours chosen per mood category.

A *Games-Howell* post hoc comparison test was conducted in order to determine which pairs of the 8 mood category means differed significantly for saturation. The results indicated a total of 22 combinations of moods that were significant. Due to limited space, only the significant pairs for mood categories pertaining to the H3 question (i.e., categories 1, 2, 5, and 6) are reported here. There was a significant main effect in preferring a saturated colour: when participants listened to the mood category 1 ($M = 1.16$, $SD = 0.37$), compared to mood category 5 ($M = 1.72$, $SD = 0.44$), with a negative effect size ($g = -1.38$); when participants listened to mood category 1 ($M = 1.16$, $SD = 0.37$), compared to mood category 6 ($M = 1.74$, $SD = 0.44$), with a negative effect size ($g = -1.45$); when participants listened to mood category 2 ($M = 1.20$, $SD = 0.40$), compared to mood category 5 ($M = 1.72$, $SD = 0.44$), with a negative effect size ($g = -1.25$); when participants listened to mood category 2 ($M = 1.20$, $SD = 0.40$), compared to mood category 6 ($M = 1.74$, $SD = 0.44$), with a negative effect size ($g = -1.30$); when participants listened to mood category 5 ($M = 1.72$, $SD = 0.44$), compared to mood category 6 ($M = 1.74$, $SD = 0.44$), with a negative effect size ($g = -0.039$). A full overview of the results, with exact significant values are provided in Table 2 within Appendix 5.

H4: Saturation & IND-COL Group

H4 proposed that depending on what type of cultural background the participant had, there would be a relationship between IND-COL group and the saturation of the colour preference they had when listening to song excerpts of varying moods. As was the case in the analysis for H3, colour preferences were pre-processed to determine whether the response was indeed saturated or desaturated. An overview of the means and standard deviations are shown in Table 2, as well as the proportions of the dependent variable among the four different IND-COL groups.

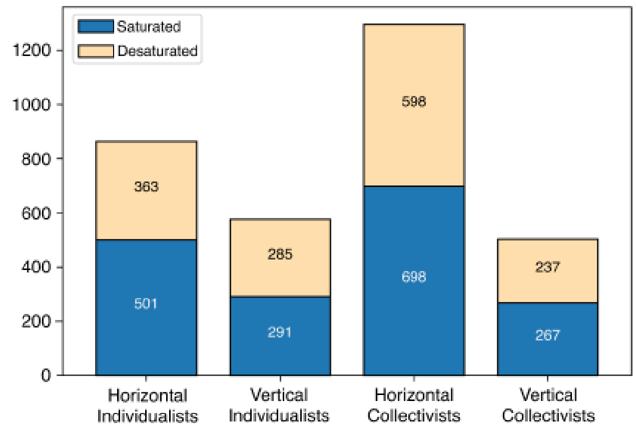

Figure 8. Stacked bar chart showing the proportion of saturated colours chosen per IND-COL group.

Since the homogeneity of variance assumption was not met, a *Welch's* ANOVA was conducted. The results revealed a statistically significant main effect, $F(3,1429.61) = 2.84$, $p = 0.04$, meaning that the null hypothesis should be rejected and the IND-COL of the participant had an effect on whether participants would prefer to select saturated or desaturated colours. A *Games-Howell* post hoc comparison test indicated 1 combination of IND-COL group that was significant, between horizontal individualists (M = 1.16, SD = 0.49) compared to vertical individualists (M = 1.20, SD = 0.50), with a negative effect size (g = -0.14). The distribution of saturation between IND-COL groups can be seen in Figure 8. All of the exact p-values for these statistical analyses can be found in Table 3 within Appendix 5.

5. STUDY 2: EVALUATING MUSIC-BASED PALETTES

Lighting systems are unlikely to have only one light source in a room, and this study focuses on creating a colour palette with the ambition of having multiple sources of light being mapped to music. This study extends the findings of Study 1, as it was focused on exploring different rules of colour harmony as a way of generatively creating colour palettes based on the music-to-colour mappings sourced from the previous study. Moreover, the main purpose of this study was to evaluate how effective each of these colour palettes were.

5.1 Method

Participants

Similar to Study 1, participants were recruited using the Prolific platform and were rewarded approximately £2.19 per submission, which corresponded to approximately £8.10 per hour. The study took approximately 15 minutes to complete. The filter criteria were the same as the first study and required participants who were proficient in English, had no form of hearing difficulties, and had normal or corrected-to-normal vision that allowed them to see colour normally. A total of 60 participants completed the study and were an average M = 25.60 (SD = 9.23) years old, and n = 34 (56%) were female (n = 25 were male, n = 1 were non-binary).

Materials

A Qualtrics survey was created to evaluate how effective each colour palette was in representing the mood of the music, where participants listened to different music while making associative pairings with colour and the music. Here, the same dataset of songs from Study 1 was used in this study. As this evaluated different palettes based on the colours selected in the previous music-to-colour mapping task, the following subsections describe the process of creating each colour palette.

Creating Generative Colour Palettes

Using a colour calculator is a common technique to generate different colours for designs and for exploring different moods through colour. Colour calculators work by using a colour wheel, a visual representation of colours, to demonstrate the geometric relationships between colours on the colour wheel. Thus, using a base colour as a reference can develop many other related colours. Reference to the colour wheel lets designers develop colour palettes using several different approaches, and in this instance, creates more colour possibilities for music-to-colour mappings.

The three approaches this study evaluated against the colours sourced from Study 1 are: (1) Analogous; (2) Split Complementary; and (3) Triadic colours. Analogous colours use the three adjacent colours on the colour wheel, making a combination that is harmonious and pleasing to the eye. Split Complementary is a variation of the complementary colour scheme, but with less tension, as it uses the two adjacent tertiary colours of the base colour's complement. Meanwhile triadic colour schemes use three evenly spaced colours around the colour wheel and tend to be quite vibrant.

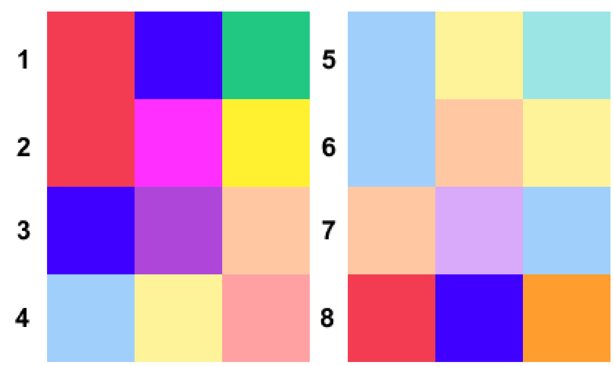

Figure 9. Resulting user-generated colour palettes sourced from the music-to-colour mapping task.

In contrast, to develop the user-generated colour palette, we used the most popular colours of what participants ranked as the most, second, and third most consistent colour choice to the song excerpt. These colours are shown in Figure 9 and a histogram showing the frequency of each colour is found in Appendix 6. In instances where there was a tie between two colours, the next colour in that category was selected based on whether it had already appeared in the colour palette. All colours had to be unique. Moreover, base colours were necessary to generate colour schemes for other colour palettes. Base colours were sourced from the user-generated colours in Study 1 and were used to generate analogous, split complementary, and triadic colour palettes for all 8 different mood categories with an online colour calculator [10]. An overview of the base colours used in this study can be found in Appendix 7. Furthermore, visuals of all the colour palettes used in this study can be seen in Appendix 8.

Procedure

The procedure of this study closely followed the procedure carried out in Study 1. Participants received the same instructions to adjust browser window settings and received the same audio warning from Study 1 before being exposed to the main evaluation task. Before they started the task, participants were given information containing an overview of the study and were asked to confirm demographic details as part of the filter criteria on Prolific.

After answering those questions, participants took part in the main evaluation task. The UI for this task is shown in Figure 10. The evaluation task involved asking the participant to listen to an audio clip enough times to get a ‘feel’ for the music. Once they had listened to it enough times, they were instructed to rate how well the colour palette represented the mood of the music on a scale of 1 to 5, with 5 being that it feel very well, and 1 being not well at all. Like in Study 1, the song excerpt played automatically and looped as soon as they started the main evaluation task. Participants submitted responses for all song excerpts in the dataset. In order to move onto the next question, it was required to give a response on each colour palette. Additionally, both the order the colour palettes were presented in the UI, and the song excerpts themselves, were randomised.

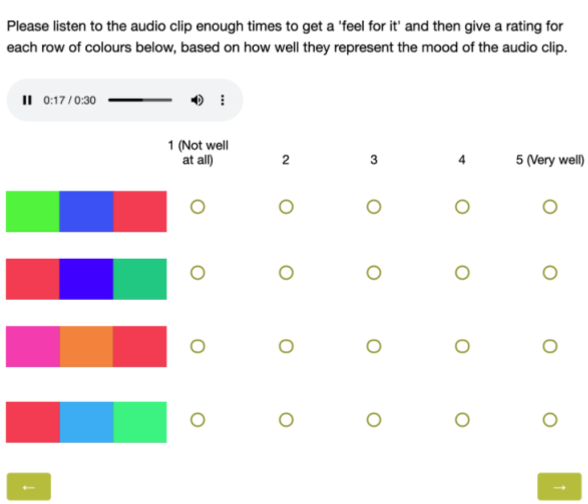

Figure 10. UI for Study 2 evaluating different colour palettes.

Design

A repeated measures ANOVA on the ratings participants provided for each colour palette was used. This included the type of colour palette as a fixed effect and participant and mood categories as random effects. This study evaluated the different methods in adding more harmonious colours and the independent variable was *colour palette type*. This variable had 4 levels: (1) user selected colours; (2) analogous colours; (3) split complementary colours; and (4) triadic colours. Since there was an insignificant finding on cultural background for music-to-colour mappings, IND-COL group as an independent variable was excluded in this study. This also simplified the analysis and allowed for re-allocation of budget toward recruiting more participants.

The dependent variable for this study is the *preference score* for each colour palette, since participants were asked to rate how well or how not so well each combination of colours represents the mood of the music (see Figure 10).

Hypothesis

Given the results of the previous study and the original research questions, this follow-up online study focused on the following hypothesis:

H5. When participants are asked to rate the suitability of colour palettes in relation to the mood of the music, then they will rate colour palettes generated from user preferences in the music-to-colour mapping task in Study 1 than other generative palettes.

5.2 Results

Descriptive Statistics

Figure 11 shows the distribution of ratings for each type of colour palette, according to how well the colour palette best represented the mood of the song excerpt was. Overall, the user-generated colour palette was rated the highest (M = 3.27, SD = 1.28), followed by the analogous colour palette (M = 3.16, SD = 1.36), split complementary (M = 1.27, SD = 1.27), and then the triadic (M = 2.72, SD = 1.33). This indicates a correlation between how well generative colour palettes, such as analogous, and how well it is rated as representing the mood of the song excerpt.

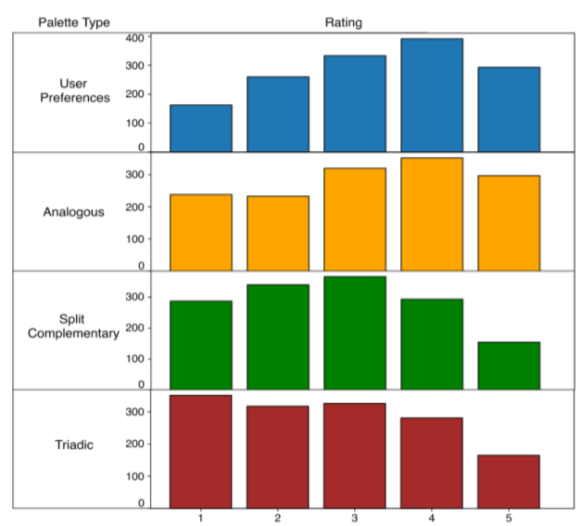

Figure 11. Histogram of ratings for user-generated, analogous, split complementary, and triadic colour palettes.

H5: Rating Suitability of Colour Palettes

H5 proposed that the rating of the suitability of a colour palette in representing the mood of a song excerpt, would be higher from user preferences than other generative palettes. To investigate this, a repeated measures ANOVA with a *Greenhouse-Geisser* correction was conducted. Using this procedure showed that there was a significant difference in ratings for each colour palette, $F(3,177) = 33.69$, $p < 0.001$, which indicates the null hypothesis should be rejected and the type of colour palette used did have on effect on the rating of how well the palettes represented the music.

To investigate the difference between each palette, a post hoc pairwise t-test with a *Bonferroni* correction was conducted. Detailed results can be seen in Appendix 9. In total, 6 paired samples t-tests were conducted. The first samples t-test indicated there was a significant difference in ratings between Analogous (M = 3.165, SD = 0.535) and Split Complementary (M = 2.783, SD = 0.538) palettes; $t(59)$ = 5.271, p = 0.001. A second paired samples t-test indicated there was a significant difference in ratings between Analogous (M = 3.165, SD = 0.535) and Triadic (M = 2.717, SD = 0.588) palettes; $t(59)$ = 5.656, p = 0.001. A third paired samples t-test indicated there was not a significant difference in ratings between Analogous (M = 3.165, SD = 0.535) and User Preferences (M = 2.717, SD = 0.588) palettes; $t(59)$ = -1.697, p = 0.57. A fourth paired samples t-test indicated there was not a significant difference in ratings between Split Complimentary (M = 2.783, SD = 0.538) and Triadic (M = 2.717, SD = 0.588) palettes; $t(59)$ = 1.515, p = 0.811. A fifth paired samples t-test indicated there was a significant difference in ratings between Split Complementary (M = 2.783, SD = 0.538) and User Preferences (M = 2.717, SD = 0.588) palettes; $t(59)$ = -7.955, p = 0.001. A sixth paired samples t-test indicated there was a significant difference in ratings between Triadic (M = 2.717, SD = 0.588) and User Preferences (M = 2.717, SD = 0.588) palettes; $t(59)$ = -7.331, p = 0.001.

6. DISCUSSION

This current study aimed to generate a music-based colour palette by gathering user-generated colour preferences based on the mood of music. Using mood and emotion as a shared characteristic toward music-to-colour mappings, follows studies carried out by key researchers in this area such as, Palmer et al. [45] Whiteford et al. [70], and Dharmapriya et al. [14]. To the author's knowledge, this current study is the first piece of research that has investigated the gathering of user-generated music-to-colour mappings using energy and valence scores to measure mood, pulled from the Spotify API. Besides focusing on the mood and emotional qualities of music, the influence of different cultural dimensions was also investigated. This was measured by using the IND-COL scale. The user-generated music-to-colour mappings from Study 1 were then used in order to evaluate how well they functioned as colour palettes for each mood category. Different techniques were employed, such as using the three most consistent colours to create new colour schemes, which followed established rules of colour harmony. Through two online studies, five hypotheses were tested. The results revealed that there was indeed a correlation between the colour preferences people had, compared to the mood of the music, and this extended to how saturated the colours were too. In terms of cultural dimensions, the data did not provide evidence that what IND-COL group participants belonged to, had an influence on colour preference. There was, however, a significant effect between IND-COL group and preference of how saturated the colour was. Finally, when evaluating different colour schemes, user-generated colours were favoured the most, quickly followed by analogous colours. The next section will discuss these findings in more detail, together with their limitations and practical applications.

Colour Preferences & the Mood of Music

The first hypothesis proposed that when participants listened to song excerpts in mood categories 1 and 2 (high valence and high energy), warmer colours would be preferred over cooler ones. The results from this study have strengthened the existing evidence, led by Palmer et al. [45] that music-to-colour associations are mediated by emotion. In this present study, there was a significant difference between colour preference and the mood of the music, which were based on relevant valence and energy data available from the Spotify API. This indicates a correlation between colour preference and mood and supports the future use of Spotify data to investigate music-to-colour associations. In relation to the first hypothesis, there were significant differences in colour choice between categories 2 (happy) and 5 (depressed) as well as between categories 5 and 6 (sad).

According to established colour theory, warm colours include red, orange, and yellow, while cooler colours are green, blue, indigo, and purple. Notably, from their positioning on the colour wheel, the colours magenta and chartreuse can be viewed as neutral in terms of being classified as either cool or warm [9]. Based on the distribution of colour preferences per mood category, the colours red, orange and yellow were picked more frequently than cooler colours such as green and blue. This was seen in both category 1 (excited) and 2. While there were slightly fewer associations of the colours purple and indigo for mood category 2, there were a lot of associations for blue and purple for category 1. This indicates that while warm colours were mainly picked for these happier moods, for these two mood categories, participants would still make associations between happy sounding music with cool, albeit vibrant, colours (indigo and purple). The reason for this is difficult to explain. A possible explanation could be down to people selecting colours they personally preferred regardless of music-to-colour pairings. However, this cannot be inferred from the results produced in this study and should be something to address in future research. Furthermore, from the post hoc test, there was not a significant difference between these two categories. For categories 5 and 6, there were more associations to cooler colours (blue, cyan, and green) than there were for warmer ones. Similar to what occurred in category 1, there were a notable number of warm colours selected (red and yellow), although cooler colours remained the most popular and there was a significant difference between the two categories.

As such, the results from this study can be considered to support the first hypothesis. Additionally, the study supports patterns identified by Palmer et al. [45] as well as Isbilen and Krumhansl [26], which both found that cooler colours were associated with music in the minor mode and warmer colours for the major. While those studies used major and minor modality as a determinant of mood, this present study brings a new perspective to measuring mood of a piece by utilising data available from the Spotify API.

The current findings regarding preferences for warmer or cooler colour preferences in relation to the mood of the music, promises to be a useful starting point toward developing a music-based colour palette using Spotify music data that is currently freely available. If this pattern is replicated in further studies, with closer application to actual home lighting systems, i.e., through in-person studies, the user-generated music-to-colour mappings from this study should be used as a place to start.

Colour Saturation & Music Mood

The third hypothesis predicted that colour preferences for mood categories 1 and 2 would more likely be associated with saturated colours, while mood categories 5 and 6 would be associated with desaturated colours. The results of the study showed that there was a significant main effect of mood on the saturation of the colour preferences for each mood category, which supports the original hypothesis.

This indicated that the level of saturation of a colour is substantially linked to the mood of the song and supports the findings by Sebba [54] and Cuiha et al. [8] on the use of saturation to convey the dissonant and consonant qualities of a song. When people are listening to music that has a low mood such as depressed, sad, or upset (i.e., categories 5, 6 and 7) then the colour which is associated with it should be desaturated. This was clearly evident when examining the different proportions of saturated colours versus desaturated colours per mood category. Furthermore, music that has a happy mood such as excited or happy moods (i.e., categories 1 and 2) should be paired with saturated colours.

An interesting aspect for this portion of the results pertains to the in-between moods serene and calm (i.e., categories 3 and 4), which were not necessarily linked to negative moods. Notably, these categories had a larger proportion of desaturated colours than they did saturated, albeit the serene mood had an almost even split. Similarly, the intense mood (category 8) had colour preferences that were selected as almost completely saturated, being selected 95% of the time for this mood category.

The implications of these findings can be used for future research to extend the existing correlation between warmer and cooler colours to include saturation levels. Since it is possible to make any colour, regardless of whether it is warm or cool, desaturated or saturated in its appearance, future studies could use this to evaluate how preferences for saturated or desaturated colours depend on the mood and feel of the music.

Influence of Cultural Dimensions

In research conducted by Palmer et al. [45], there were no cultural differences in music-to-colour mappings between US and Mexican participants. This initiated the idea of cultural generality, as proposed by Whiteford et al., in terms of emotional mediation in music-to-colour associations [70]. In this present study there were two hypotheses that aimed to investigate links between cultural background to colour preference (H2) and to saturation (H4). It was found that there was not a statistically significant difference between colour preference and mood category across different cultures as measured by the IND-COL scale, but only a marginal difference. This supports the results of the research described above, in regard to colour preference.

However, in regard to saturation, this was not the case and the current study's results indicated there was statistically significant difference between culture and saturation preference. While this is still not conclusive evidence that cultural dimensions have an effect on colour preferences, the statistical significance for H4 indicates culture may still have an influence on music-to-colour associations. As such, even though the data from this study certainly cannot indicate cultural influences in colour preferences, the present author argues that it is worth conducting more exploration in future research. Although this is discussed further under the limitations section, this current study shares some of the same limitations experienced in the research by Palmer et al. where the strength of the cultural generalisation was unclear since people in Mexico would have had extensive exposure to Western music. In this study, even though IND-COL was determined, the study itself was only available to English speakers and lacked ecological validity. Since this study was conducted in English, the participants recruited for this survey may have had a level of exposure to Western culture.

How music-to-colour associations are perceived in terms of culture is an important factor to explore, since home lighting systems are growing in popularity in many different parts of the world. While this research does not contain data to find significance of culture on the effect for colour preference, it did find an effect for saturation suggesting that further exploration in this area would be useful.

Evaluating Colour Palettes

The final section of this research focused on evaluating how well different colour palette techniques would perform against one another. The hypothesis for this research area predicted that colour palettes generated from user preferences in the first study would be rated the highest. The average rating of the different colour palette types per mood category indicated support for this hypothesis. Unsurprisingly, the results indicated that there was a correlation between how well human-extracted colours from music are rated as representing the mood and energy of the music.

Moreover, in terms of the generated colour palettes, the analogous colour palette was the second highest rated. This suggests that in potential scenarios where user-generated music-to-colour mappings are exhausted, a promising option to produce more music-to-colour associations would be through the analogous colour harmony schemes compared to either split complementary and triadic.

In practical application, and in the context of home lighting systems, more colours available can allow for different light sources to display multiple colours at the same time or change sequentially to suitable sections of the music. While analogous colours were the highest rated generative palette, the use of different colour palettes to represent the music needs further research, particularly in evaluating the coalescence of music and colour under different contexts.

Limitations

There are a multitude of limitations for this study that should be addressed. The largest and most obvious limitation was that, due to time and budget constraints, the testing of music-to-colour mappings was never tested on actual LED lighting systems. This is important for a number of reasons. Firstly, it means that this study lacked ecological validity and secondly, the perception of colours is different from a light than it is on a computer monitor. This study relied on crowdsourcing colours using the Prolific platform on each participants own computer. In the field, most monitors vary widely in colour and result in colours looking very different to each other. As this study was based online, this was impossible to control for. As a result, the music-based colour palette developed in this study can only be viewed as a starting point for future research and cannot be generalisable to home lighting systems without in-person testing that uses actual lighting hardware, or best alternative.

Lack of transparency over how the Spotify API calculates its audio feature scores can be considered another substantial limitation of this study. As discussed in the method section, valence and energy scores were an average for each song. While this study took loudness scores closest to the average as a way to decide what section to test, only Spotify knows exactly how valence and energy are calculated since it is proprietary software. This creates a huge reliance on the platform, which could make it difficult to use again in future research since the values of the audio features can change depending on what Spotify sees fit. While there is future potential to use this reference data for more research, this might not be suitable in the long run.

Another limitation concerns the recruitment of participants. The first study in particular had a significant gender imbalance where almost three quarters of the sample were female. As Prolific randomly assigned participants, this could not be controlled for and as such, should be treated as an implication of the music-to-colour mapping data. Another limitation concerned recruiting participants from different cultural backgrounds. As mentioned in a previous section of the discussion section, the study was conducted in English on participants who were fluent in the language. This suggests some level of exposure to Western culture, which Whiteford et al. cites as a reason for a lack of evidence toward cultural influences on music-to-colour mappings [70]. Moreover, the songs used in this study were all in English and mostly familiar to Western audiences, which could mean some responses being answered based on their past personal experiences with the song. In terms of recruitment, in this study, the number of participants per IND-COL group was unequal and this could have had an effect on the influence of cultural background on music-to-colour mappings.

Future Work

Despite its limitations, this study can be viewed as a starting point for future research on music-to-colour associations. An important area to focus on is how the user-generated colours from this research would fit in the real-world context of listening to an entire song as well as how the colours would be experienced using home lighting system hardware. Even though this study has shown the potential use of Spotify data, more rigorous testing could benefit from a partial deviation from the Spotify API for the perceptual measures of valence and energy to calculate the mood of the music, since they are currently only available as an average. Unless this changes, custom audio analysis of audio features should be considered to complement Spotify data in determining the mood of a song on a section-by-section basis. This can enable research to evaluate how well user-generated colours represent the entire song, rather than only one section as this is a limitation of the current study. Moreover, future research should consider how these colours would coalesce the lighting with the sound of a song in a physical space. Past research suggests contextual factors influence how people enjoy listening to music with lighting systems [28], and so it would be valuable to conduct further research under real-world settings and even longitudinally. It might also be beneficial to see whether music-to-colour mappings follow a different pattern if the study was designed to be personalised to the participant. Ideally, a participant could make music-to-colour mappings on their own music libraries and conduct the study in their native language.

7. CONCLUSION

This research aimed to gather user-generated music-to-colour associations in order to investigate how they are influenced by different moods of music and cultural background. It then built on these findings to develop music-to-colour-mappings into a palette of colours in a follow-up study. The current research contributes to the identification of different factors towards generating a music-based colour palette and results in an initial set of colours from users that fit eight different music moods (see Appendix 8). This knowledge of initial music-to-colour mappings is necessary in order to design and create home lighting systems that can support coloured light effects that synchronise with music playback.

The key takeaways of this research are the following:

(1) The mood of a song has a significant effect on the colours that people will make associations with it.
(2) People tend to associate warmer colours to music of a happy mood, while they will associate cooler colours to music of a sad mood.
(3) People tend to associate saturated colours to excited, happy and also intense music. Conversely people associate desaturated colours to sad, depressed but also calm and serene music.
(4) Cultural background, measured by IND-COL scale, does not have a significant effect on colour choice, but does so for colour saturation.
(5) Analogous colour palettes based on initial music-to-colour mappings are the best alternative to a user-generated colour palette.

While these music-to-colour associations represent preferences for only a section of a song that fits within a certain mood, this research can be used as a framework for future studies that involve coloured effects for home lighting systems.

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APPENDIX 1: FULL LIST OF SONGS USED

Cat.	Song	Artist	Energy	Valence	Start-end (sec)	Duration (sec)
1	Get Ready	Congo Natty	0.92	0.75	11-31	19
1	Livin' On A Prayer	Bon Jovi	0.89	0.80	16-46	30
1	Sweet Child O' Mine	Guns N' Roses	0.91	0.63	16-27	11
2	Billie Jean	Michael Jackson	0.65	0.85	54-70	16
2	Hound Dog	Elvis Presley	0.76	0.95	116-136	20
2	September	Earth, Wind & Fire	0.83	0.98	20-46	26
3	Dreams	Fleetwood Mac	0.34	0.79	0-18	18
3	Green Onions - 45 Version	Booker T. & the M.G.'s	0.38	0.89	47-70	23
3	Who Is He (& What Is He to You)?	Bill Withers	0.31	0.96	19-48	29
4	Bizarre Love Triangle	The Macarons Project	0.20	0.63	22-52	30
4	Please Keep Loving Me	James TW	0.17	0.59	33-47	14
4	Sweet Caroline	Neil Diamond	0.13	0.58	103-126	22
5	Heaven Knows, Right?	Benjamin Gustafsson	0.03	0.27	224-245	21
5	Mirou	Sumie	0.05	0.08	96-115	19
5	Unspoken	Aaron Smith	0.17	0.35	17-34	17
6	1972	Josh Rouse	0.46	0.27	31-62	30
6	Orange Sky	Alexi Murdoch	0.15	0.13	100-128	29
6	Stairway to Heaven	Led Zeppelin	0.34	0.20	135-160	26
7	Nothing Compares 2 U	Sinead O'Connor	0.57	0.16	160-168	8
7	Something On Your Mind	Karen Dalton	0.60	0.26	20-36	16
7	Trouble	Coldplay	0.55	0.20	16-29	13
8	Painkiller	Judas Priest	0.99	0.10	90-102	13
8	Wait and Bleed	Slipknot	1.00	0.33	135-148	13
8	Your Betrayal	Bullet For My Valentine	0.88	0.37	265-280	15

APPENDIX 2: MODIFIED BCP-37 COLOURS USED

Selected colour values based off of the BCP-37 in both CIE xyY Colour Space and HEX.

Colour	x	y	Y	HEX code
Sat. Red	0.549	0.313	22.93	FF96FF
Desat. Red	0.407	0.326	49.95	FF30FF
Sat. Orange	0.513	0.412	49.95	96E1B9
Desat. Orange	0.399	0.366	68.56	E2EE9A
Sat. Yellow	0.446	0.472	91.25	AD99FF
Desat. Yellow	0.391	0.413	91.25	4000FF
Sat. Chartreuse	0.357	0.420	79.90	AE47D9
Desat. Chartreuse	0.387	0.504	68.56	FF9D2F
Sat. Green	0.254	0.449	42.40	22A9EF
Desat. Green	0.288	0.381	63.90	7AC9C5
Sat. Cyan	0.226	0.335	49.95	00C882
Desat. Cyan	0.267	0.330	68.56	C8E53D
Sat. Blue	0.200	0.23	34.86	F33C51
Desat. Blue	0.255	0.278	59.25	FFF130
Sat. Indigo	0.174	0.076	7.203	FFA0A3
Desat. Indigo	0.283	0.242	38.196	FFF399
Sat. Purple	0.272	0.156	18.43	A1CFFB
Desat. Purple	0.290	0.242	49.95	9BE5E4
Sat. Magenta	0.363	0.187	30.431	FFC8A3
Desat. Magenta	0.356	0.257	50.176	D9A9FA

APPENDIX 3: IND-COL QUESTIONNAIRE ITEMS

Questions used and the scale in order to identify cultural dimension of the participant.

Horizontal Individualism (HI) items:

1. I'd rather depend on myself than others.
2. I rely on myself most of the time; I rarely rely on others.
3. I often do 'my own thing'.
4. My personal identity, independent of others, is very important to me.

Vertical Individualism (VI) items:

1. It is important that I do my job better than others.
2. Winning is everything.
3. Competition is the law of nature.
4. When another person does better than I do, I get tense and aroused.

Horizontal Collectivism (HC) items:

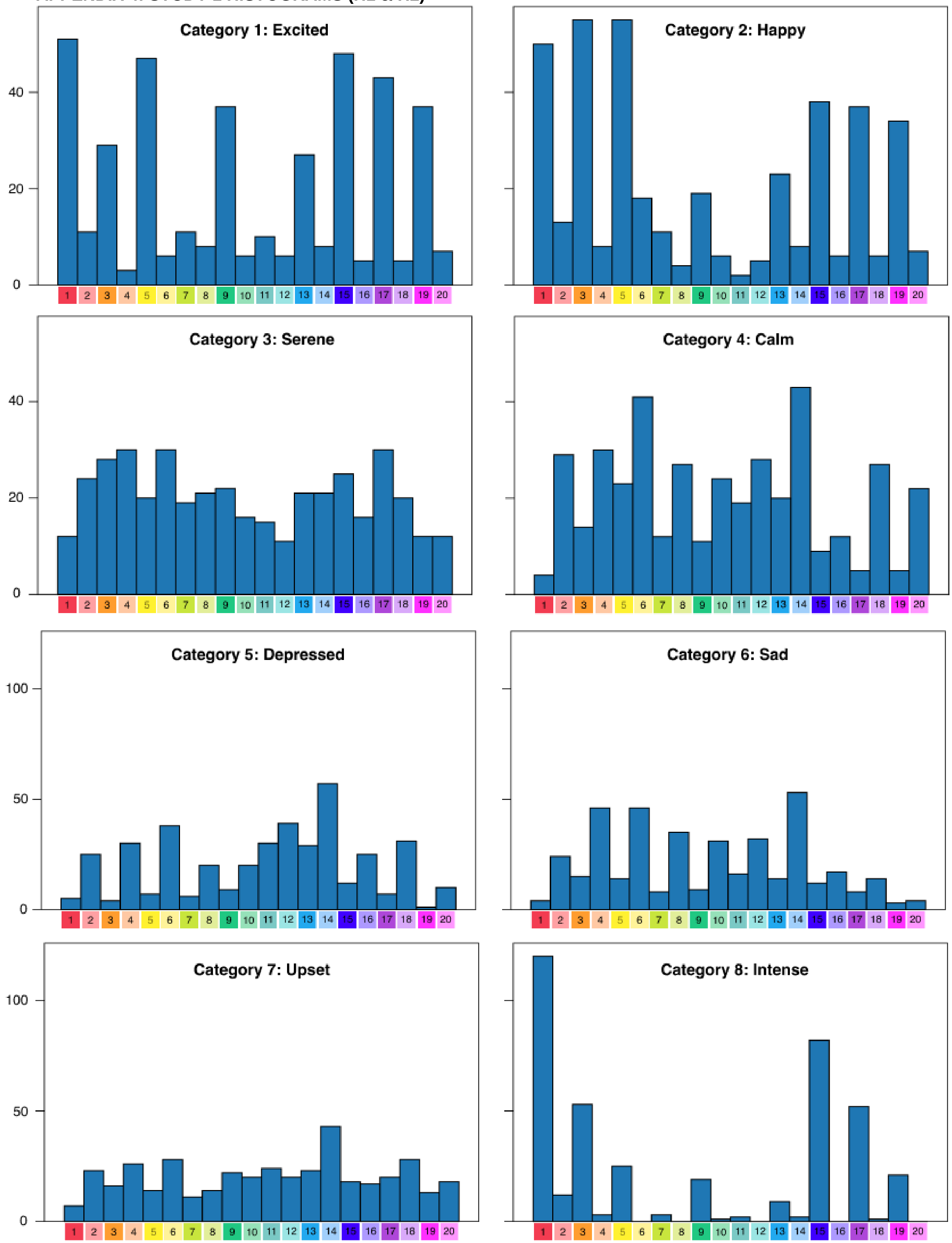
1. If a coworker gets a prize, I would feel proud.
2. The well-being of my coworkers is important to me.
3. To me, pleasure is spending time with others.
4. I feel good when I cooperate with others.

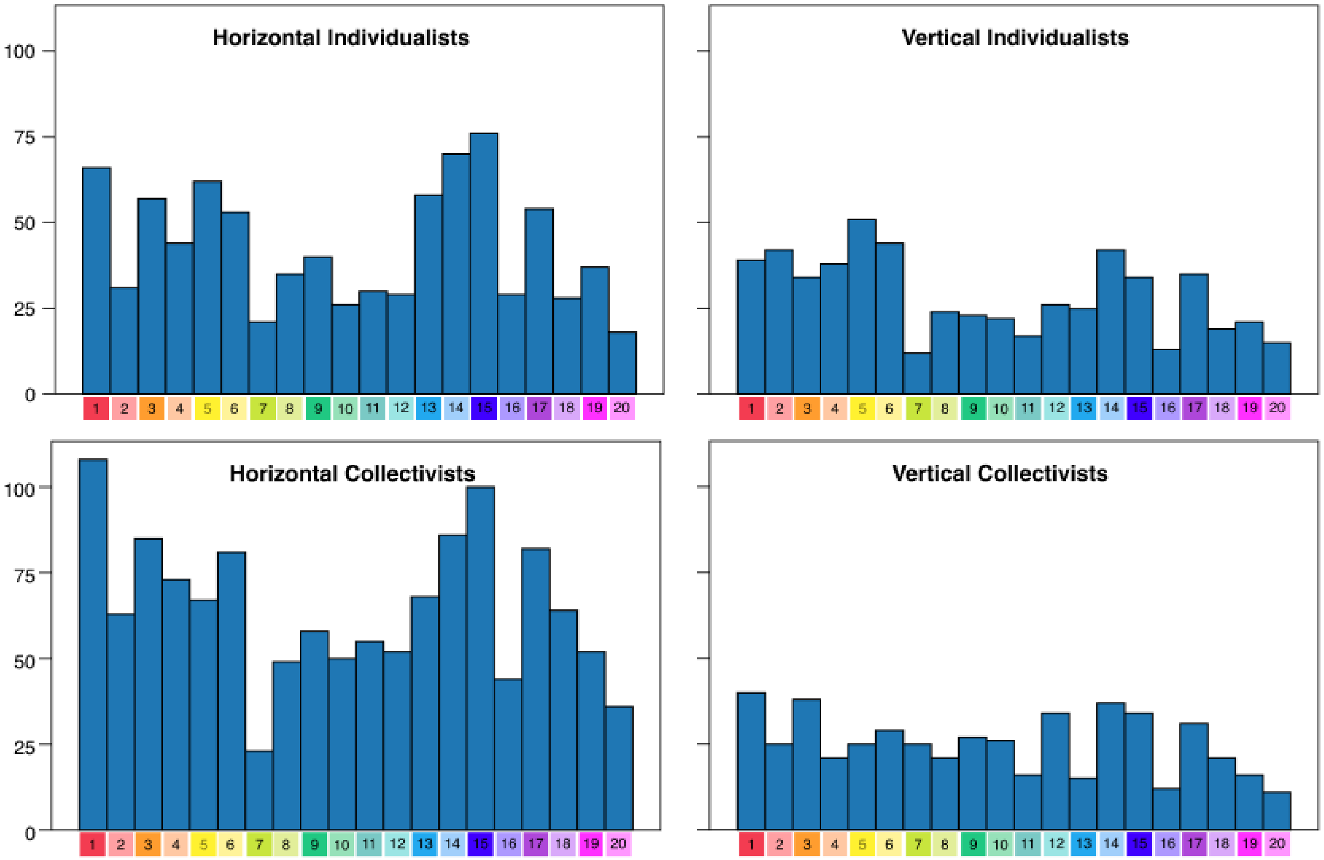
Vertical Collectivism (VC) items:

1. Parents and children must stay together as much as possible.
2. It is my duty to take care of my family, even when 1 have to sacrifice what I want.
3. Family members should stick together, no matter what sacrifices are required.
4. It is important to me that I respect the decisions made by my groups.

Scale: *Items should be randomised prior to administering the questionnaire. All items are answered on a 9-point scale, ranging from 1 = never or definitely no and 9 = always or definitely yes.*

APPENDIX 4: STUDY 1 HISTOGRAMS (H1 & H2)




Horizontal Individualists
Vertical Individualists
Horizontal Collectivists
Vertical Collectivists
100
75
50
25
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20

APPENDIX 5: DETAILED RESULTS (STUDY 1)

Post Hoc Analysis of H1

(A) Category	(B) Category	Mean Diff. (A-B)	Std. Error	Sig.	Effect Size (Hedges')
1 (Excited)	2 (Happy)	1.007	0.444	0.311	0.1594
1 (Excited)	3 (Serene)	0.124	0.418	0.900	0.0207
1 (Excited)	4 (Calm)	0.054	0.409	0.900	0.0093
1 (Excited)	5 (Depressed)	-0.731	0.396	0.575	-0.1297
1 (Excited)	6 (Sad)	0.669	0.392	0.658	0.12
1 (Excited)	7 (Upset)	-0.844	0.412	0.452	-0.1439
1 (Excited)	8 (Intense)	1.842	0.461	0.002*	0.2804
2 (Happy)	3 (Serene)	-0.884	0.424	0.428	-0.1464
2 (Happy)	4 (Calm)	-0.953	0.415	0.296	-0.1614
2 (Happy)	5 (Depressed)	-1.738	0.402	0.001*	-0.3038
2 (Happy)	6 (Sad)	-0.338	0.398	0.900	-0.0597
2 (Happy)	7 (Upset)	-1.852	0.418	0.001*	-0.3112
2 (Happy)	8 (Intense)	0.835	0.466	0.610	0.1256
3 (Serene)	4 (Calm)	-0.069	0.387	0.900	-0.0125
3 (Serene)	5 (Depressed)	-0.854	0.374	0.302	-0.1606
3 (Serene)	6 (Sad)	0.546	0.369	0.796	0.1038
3 (Serene)	7 (Upset)	-0.968	0.391	0.207	-0.1739
3 (Serene)	8 (Intense)	1.719	0.442	0.003*	0.2727
4 (Calm)	5 (Depressed)	-0.785	0.363	0.376	-0.1519
4 (Calm)	6 (Sad)	0.615	0.358	0.654	0.1204
4 (Calm)	7 (Upset)	-0.899	0.381	0.262	-0.1658
4 (Calm)	8 (Intense)	1.788	0.433	0.001*	0.2896
5 (Depressed)	6 (Sad)	1.400	0.343	0.001*	0.2863
5 (Depressed)	7 (Upset)	-0.114	0.366	0.900	-0.0218
5 (Depressed)	8 (Intense)	2.573	0.421	0.001*	0.4291
6 (Sad)	7 (Upset)	-1.514	0.362	0.001*	-0.2935
6 (Sad)	8 (Intense)	1.173	0.417	0.094	0.1974
7 (Upset)	8 (Intense)	2.686	0.436	0.001*	0.4322

Table1. Detailed post hoc results of the statistical analysis of H1.

**significant.*

Post Hoc Analysis of H3

(A) Category	(B) Category	Mean Diff. (A-B)	Std. Error	Sig.	Effect Size (Hedges')
1 (Excited)	2 (Happy)	-0.040	0.027	0.805	-0.103
1 (Excited)	3 (Serene)	-0.336	0.031	0.001*	-0.764
1 (Excited)	4 (Calm)	-0.538	0.029	0.001*	-1.293
1 (Excited)	5 (Depressed)	-0.568	0.029	0.001*	-1.390
1 (Excited)	6 (Sad)	-0.585	0.028	0.001*	-1.450
1 (Excited)	7 (Upset)	-0.425	0.031	0.001*	-0.975
1 (Excited)	8 (Intense)	0.114	0.021	0.001*	0.378
2 (Happy)	3 (Serene)	-0.296	0.032	0.001*	-0.653
2 (Happy)	4 (Calm)	-0.499	0.030	0.001*	-1.156
2 (Happy)	5 (Depressed)	-0.528	0.030	0.001*	-1.247
2 (Happy)	6 (Sad)	-0.546	0.029	0.001*	-1.302
2 (Happy)	7 (Upset)	-0.385	0.032	0.001*	-0.857
2 (Happy)	8 (Intense)	0.153	0.023	0.001*	0.478
3 (Serene)	4 (Calm)	-0.203	0.034	0.001*	-0.421
3 (Serene)	5 (Depressed)	-0.232	0.033	0.001*	-0.489
3 (Serene)	6 (Sad)	-0.249	0.033	0.001*	-0.531
3 (Serene)	7 (Upset)	-0.089	0.035	0.178	-0.179
3 (Serene)	8 (Intense)	0.449	0.027	0.001*	1.168
4 (Calm)	5 (Depressed)	-0.030	0.032	0.900	-0.065
4 (Calm)	6 (Sad)	-0.047	0.032	0.788	-0.105
4 (Calm)	7 (Upset)	0.114	0.034	0.017*	0.238
4 (Calm)	8 (Intense)	0.652	0.025	0.001*	1.821
5 (Depressed)	6 (Sad)	-0.017	0.031	0.900	-0.039
5 (Depressed)	7 (Upset)	0.143	0.033	0.001*	0.305
5 (Depressed)	8 (Intense)	0.682	0.025	0.001*	1.953
6 (Sad)	7 (Upset)	0.161	0.033	0.001*	0.344
6 (Sad)	8 (Intense)	0.699	0.024	0.001*	2.037
7 (Upset)	8 (Intense)	0.538	0.027	0.001*	1.417

Table 2. Detailed post hoc results of the statistical analysis of H3.

**significant.*

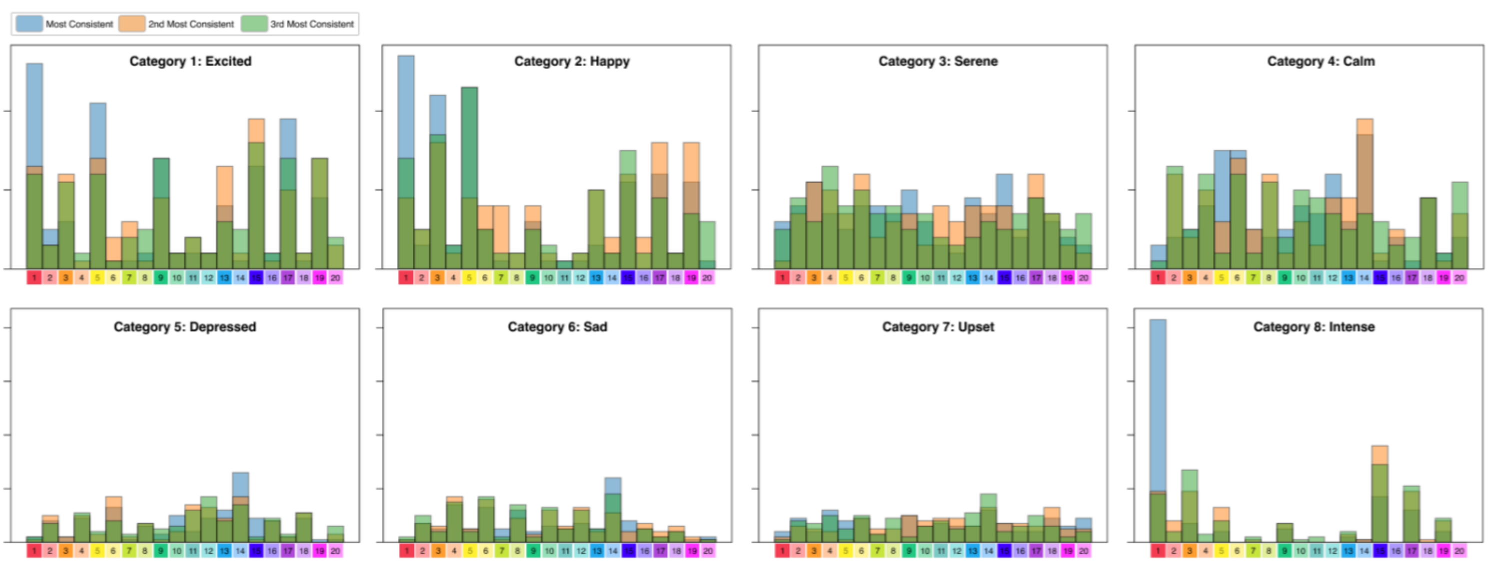
Post Hoc Analysis of H4

(A) IND-COL	(B) IND-COL	Mean Diff. (A-B)	Std. Error	Sig.	Effect Size (Hedges')
Hor. Individualist	Ver. Individualist	-0.075	0.027	0.028*	-0.150
Hor. Individualist	Hor. Collectivist	-0.041	0.022	0.230	-0.083
Hor. Individualist	Ver. Collectivist	-0.050	0.028	0.276	-0.101
Ver. Individualist	Hor. Collectivist	0.033	0.025	0.537	0.067
Ver. Individualist	Ver. Collectivist	0.025	0.031	0.833	0.049
Hor. Collectivist	Ver. Collectivist	-0.009	0.026	0.900	-0.018

Table 3. Detailed post hoc results of the statistical analysis of H4.

**significant.*

APPENDIX 6: HISTOGRAM OF THE TOP VALUES OF MOST, SECOND, THIRD MOST CONSISTENT



APPENDIX 7: HEX CODE VALUES OF COLOUR PALETTES

User-Generated

Cat.	Colour 1	Colour 1 HEX code	Colour 2	Colour 2 HEX code	Colour 3	Colour 3 HEX code
1	Sat. Red	F33C51	Sat. Blue	4000FF	Sat. Green	20C882
2	Sat. Red	F33C51	Sat. Magenta	FF30FF	Sat. Yellow	FFF130
3	Sat. Blue	4000FF	Sat. Purple	AE47D9	Desat. Orange	FFC8A3
4	Desat. Blue	A1CFFB	Desat. Yellow	FFF399	Desat. Red	FFA0A3
5	Desat. Blue	A1CFFB	Desat. Yellow	FFF399	Desat. Cyan	9BE5E4
6	Desat. Blue	A1CFFB	Desat. Orange	FFC8A3	Desat. Yellow	FFF399
7	Desat. Orange	FFC8A3	Desat. Purple	D9A9FA	Desat. Blue	A1CFFB
8	Sat. Red	F33C51	Sat. Blue	4000FF	Sat. Orange	FF9D2F

Analogous

Category	Base Colour	Colour 1 HEX code	Colour 2 HEX code	Colour 3 HEX code
1	Sat. Red	F33CAD	F3823C	F33C51
2	Sat. Magenta	9830FF	FF3098	FF30FF
3	Sat. Blue	0040FF	BF00FF	4000FF
4	Desat. Blue	A1FBFA	A1A3FB	A1CFFB
5	Desat. Yellow	FFC099	D8FF99	FFF399
6	Desat. Orange	FFA3AC	FFF6A3	FFC8A3
7	Desat. Purple	B1A9FA	FAA9F2	D9A9FA
8	Sat. Orange	FF362F	F8FF2F	FF9D2F

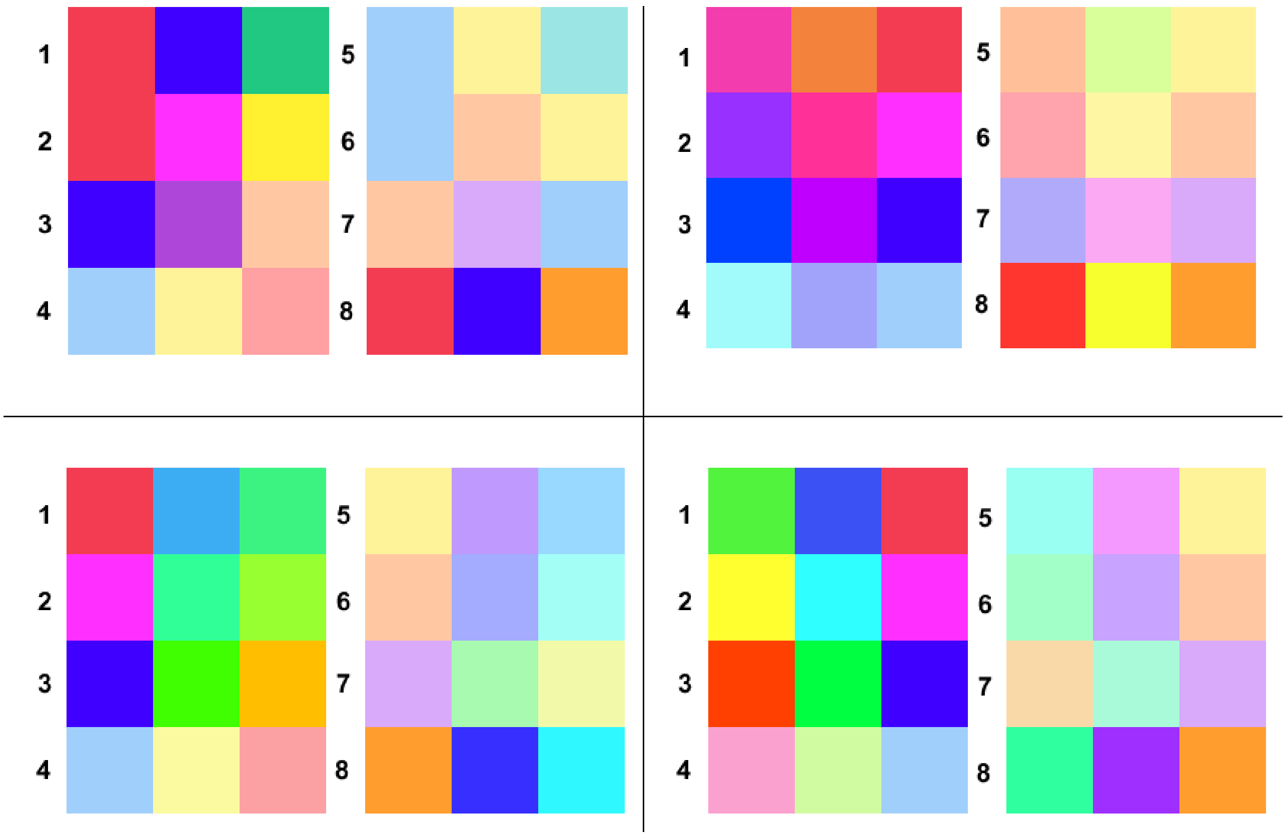
Split Complementary

Category	Base Colour	Colour 1 HEX code	Colour 2 HEX code	Colour 3 HEX code
1	Sat. Red	F33C51	3CADF3	3CF382
2	Sat. Magenta	FF30FF	30FF98	98FF30
3	Sat. Blue	4000FF	40FF00	FFBF00
4	Desat. Blue	A1CFFB	FBFAA1	FBA1A3
5	Desat. Yellow	FFF399	C099FF	99D8FF
6	Desat. Orange	FFC8A3	A3ACFF	A3FFF6
7	Desat. Purple	D9A9FA	A9FAB1	F2FAA9
8	Sat. Orange	FF9D2F	362FFF	2FF8FF

Triadic

Category	Base Colour	Colour 1 HEX code	Colour 2 HEX code	Colour 3 HEX code
1	Sat. Red	51F33C	3C51F3	F33C51
2	Sat. Magenta	FFFF30	30FFFF	FF30FF
3	Sat. Blue	FF4000	00FF40	4000FF
4	Desat. Blue	FBA1D0	D0FBA1	A1CFFB
5	Desat. Yellow	99FFF3	F399FF	FFF399
6	Desat. Orange	A3FFC8	C8A3FF	FFC8A3
7	Desat. Purple	FAD9A9	A9FAD9	D9A9FA
8	Sat. Orange	2FFF9E	9E2FFF	FF9D2F

APPENDIX 8: COLOUR PALETTES USED IN STUDY 2



Colour palettes used in Study 2: *User-generated* (TL), *Analogous* (TR), *Split Complementary* (BL), *Triadic* (BR).

APPENDIX 9: DETAILED RESULTS (STUDY 2)

(A) Palette	**(B) Palette**	***M* (A)**	***SD* (A)**	***M* (B)**	***SD* (B)**	**T**	**df**	**Sig.**
Analogous	Split Comp.	3.165	0.535	2.783	0.538	5.271	59	0.001*
Analogous	Triadic	3.165	0.535	2.717	0.588	5.656	59	0.001*
Analogous	User Pref.	3.165	0.535	3.274	0.519	-1.697	59	0.570
Split Comp.	Triadic	2.783	0.538	2.717	0.588	1.515	59	0.811
Split Comp.	User Pref.	2.783	0.538	3.274	0.519	-7.955	59	0.001*
Triadic	User Pref.	2.717	0.588	3.274	0.519	-7.331	59	0.001*

Detailed results of the statistical analysis of H5.

**significant.*