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# A NEW APPROACH IN VISUALISING HUMAN EMOTIONS USING BRAINWAVE-DRIVEN GENERATIVE ART

Lee Kin Keong[1*], Jolaina M. Nasseri[2]

[1] Department of Creative Industries, Universiti Tunku Abdul Rahman, Malaysia
Email: leekk@utar.edu.my
[2] Pascasiswazah, Akademi Seni Budaya dan Warisan Kebangsaan, Malaysia
Email: jolaina@aswara.edu.my
[*] Corresponding Author

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**Abstract:**

This paper delves into the exciting potential of real-time generative art as a powerful tool for visualizing emotion-based data, especially within creative collaborations. The research specifically narrowed on generative art, affective data, and creative teamwork. The main aim is to figure out just how generative art can effectively capture the intricate nature of human emotions and stand as a truly valid method for data visualization. A qualitative approach is chosen in getting participants involved in a self-tracking process. An electroencephalogram (EEG) device is used, specifically the Muse 2 headband, to get real-time visualizations of emotions. The data collected included brainwave activity and reflections on personal life events. Focusing on two key emotions: enjoyment and sadness, using text to stir up those personal experiences. The different brainwave frequencies, Alpha, Beta, Delta, Theta, and Gamma were then mapped directly to specific visual parameters of a 3D torus shape. These generative visuals can really be used as a fantastic data visualization method for some deep analysis into human mental well-being. Generative art can indeed capture a wide array of emotions and provides real-time visualizations of complex data without the removal of data noise. This research clearly showed that enjoyment and sadness each have its own distinct visual characteristics, which are reflected in the motion and visual qualities of the generated art. Crucially, the generative system actually considers that data noise instead of removing it, giving a much more authentic representation of emotions. Participants had heightened awareness and concentration while collaborating creatively. Ultimately, this research concludes that real-time generative art is a super effective way to visualize data and capture the intricate complexity of human emotions. By using raw brainwave data, the creation of unique visualizations of personal experiences without needing verbal or written explanations. This method truly offers a deeper understanding of emotions, which is vital for assessing mental well-being.

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**Keywords:**

Brainwave, Data, Digital, Emotions, Visualisation, Well-being.

## Introduction

This research explores the innovative intersection of generative art, human emotions and creative collaboration in visualizing human emotions in real-time. This research investigates the potential of generative art as a method for capturing the complexities of human emotions and its use as a valid form of data visualization (Nguyen, 2022; Eby, 2020). The rapid digitalization of daily activities and the increasing interest in applying new approaches such as implications of immersive technologies in the healthcare sector and its built environment (Yang, 2023). Advanced visualization enables the personalization of information in real-time, evolving into a personal administers process based on user-generated data (Hasselgren, 2021).

This research explores how the creative collaboration of art and data in the emerging technology can enrich the experience of understanding the value form and function in design.This research explores how the creative collaboration of art and data in the emerging technology can enrich the experience of understanding the value form and function in design. This paper focuses on the ability of generative art in capturing complex data, such as human emotions by using real-time data input from brainwave activity. The research utilizes qualitative approach, involving participants in self-tracking process using electronic devices such as EEG Muse 2 headband, to produce visualizations of their emotions. This research examines how textual stimuli can evoke personal and authentic emotional responses which are translated into generative visuals. The research also addresses the potential of generative art to serve as a digital asset and a data visualization method for studying human well-being.

The methodology involves processing raw brainwave data through Mind Monitor application which will be parsed through TouchDesigner, mapping the brain frequencies to specific visual parameters. This approach leads to the generation of unique visual artifacts that reflect the emotional states of the participants. This research extends the idea of data visceralization, aiming to create more meaningful experience and representation by embedding emotions into data visualization (Lee et al., 2020). The combination of inventiveness in generative art through emerging technologies creates the expressive potential of processing cultural data in a digital environment (Grba, 2021).

The research questions in this research focuses on

1. Can generative art capture the complexity of represented data such as emotions?
2. How can generative art be developed as a data visualisation method for capturing human emotions?
3. How effective is generative art in creating a meaningful representation of personal data?

This paper contributes to the body of knowledge of the intersection between creative arts, data visualization and human-computer interaction, offering insights into the potential of generative art as a tool for visualising and understanding complex emotional data. This research serves as a guide for researchers to incorporate generative art as a data visualization method, especially in qualitative data analysis. For the general public, this research will heighten their knowledge

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in understanding generative art and its implications in visualizing their emotional well-being in the digital realm.

## Literature Review

### *Generative Art*

Generative art is an artistic practice that employs an autonomous system, such as a computer program or set of rules to create artworks. The emulation of natural complexity in the creation of artificial events or humanistic approaches in reference to nature. (Soddu, 2022). It is distinguished as an underlying creative logic rather than specific technique. The approach allows artists to set parameters, which the system will use to autonomously generate variables and outputs (Mendez, 2021). The origins of generative art can be traced back to early forms of art randomization, such as Wolfgang Amadeus Mozart's Musikalisches Würfelspiel, and further developed through the 19th and 20th centuries with artist like Paul Cezanne, who influenced the principle of Cubism (Hoy, 2017; Bailey, 2018). The development of computer technology significantly expanded generative art's capabilities, creating new possibilities for artistic expression within a collaborative environment (Huang, 2023). The interaction between humans and machines is the key aspect of this research, where artists define parameters and curate outputs while leveraging the autonomous capacity of the system (McCormack et al, 2024; Kovacic et al, 2023). *Assembly Lines* is a live performing installation by Sougwen Chung that explores the feedback loop between human and machine. A 30-minute performance merging robotic collaborators in a visual art installation (Figure 1).

**Figure 1: Assembly Lines (2023) by Sougwen Chung**

Data-driven art is a significant form of generative art that utilizes data as a primary source of material and inspiration, going beyond visualization (Benzi, 2023). It transforms varied data sources, including scientific datasets, economic figures, historical events, social media trends, and even personal biometric information, into interactive and meaningful representation of experiences (Kovacic et al., 2023). Generative art is employed to translate data into new artistic forms like painting, sculptures, or music. Demonstrates the translation of auditory art form in

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a form of visual data (Hisariya et al., 2024). The use of algorithms to create artworks based on data and rules is the key aspect of data-driven art, resulting in fractal art, patterns, and abstract compositions (Fredericks et al., 2024). A primary challenge in generative art is the interpretation of abstract data representations, which often requires supporting information to justify the outputs.

Generative art has evolved into many different forms and gaining global presence, installations such as Refik Anadol's Machine Hallucination have been projected in The Sphere, Las Vegas in 2023. The interplay of human and machine with intangible elements such as emotions suggests importance of data handling (Figure 2). Ethical considerations and data privacy are crucial when handling personal data sources (Fiesler et al., 2024). Generative art is also seen as a dynamic area of exploration, where artistic vision and science merged, resulting in interactive installations that involve real-time feedback data streams and user feedback (Rempe et al., 2021).

| Title | Author | Year | Theme | Key Feature / Technique |
|---|---|---|---|---|
| Visual Valence (VV) Study | Sadeghi et al. | 2024 | Direct sensing of emotion from basic visual features | Machine learning model (VVM) trained on emotionally charged photographs |
| Machine Hallucinations - Sphere | Refik Anadol | 2023 | Transforming data into abstract visual landscapes | Artificial Intelligence (AI) to 'hallucinate', generative data sculptures. AI-driven generative art using urban datasets |
| Assembly Lines | Sougwen Chung | 2023 | Interplay between robotic and biofeedback. | Custom robotic system that connects to EEG headset. |
| Mood of the Planet | Sorenson et al. | 2022 | Visualizing global emotions | Interactive sculpture using colored light and sound based on aggregated emotional data |
| RisingEMOTIONS | Aragon et al. | 2021 | Visualizing community emotions | Public art installation encoding emotions from an online survey into physical artifacts |

**Figure 2: Past Exhibitions of Generative Art**

Generative art with artificial intelligence is enabling the creation of entirely new artistic styles and aesthetics that were previously impossible to achieve manually. This is leading in blurring the lines between traditional art forms and computationally generated art (Zheng et al., 2024). Generative art is being integrated with other technologies, such as virtual reality (VR) and augmented reality (AR), in creating immersive and interactive experiences (Yevsyeyev & Hrabovskyi, 2024). This expands the possibilities for artistic expression beyond static images and videos. Generative art is increasingly being informed by large datasets, allowing the creation of personalized and customized artworks. Opening up new possibilities for interactive

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and adaptive art experiences. Generative art with the help of AI is finding applications in various domains beyond art and even in healthcare (Sai et al., 2024).

**Data Visualisation**

Data visualization is the process of creating graphic displays that represent data that functions to engage audiences and providing knowledge (Unwin, 2020). The primary goal is to present complex data and statistics into a descriptive and simplified form, revealing patterns and gaps that statistical models might not be able to display (Hand, 2019). Traditional data visualization often relies on charts and graphics; modern techniques combine art and technology to create accessible and scalable presentations (Alshehhi et al., 2022). Datasets of 360 degrees videos with continuous physiological measurements, subjective emotional ratings and motion traces directly address the emotional aspect of data visualisation (Guimard et al., 2022). Generating new knowledge and making discoveries from large datasets has been emphasized and visualisation is a crucial component of making these discoveries understandable and trustworthy (Allen et al., 2023). The multimodal data integration demonstrates the use of visualization to integrate and present multimodal data, this helps in enhancing understanding and allows for more comprehensive analysis (Fernandes et al., 2021). Maps, colors, patterns and animation are the different types of visualisation employed to communicate information and evoke emotions (Zoss, 2022; Alshehhi et al., 2022). The demand for real-time visualization of dynamic data is growing across various fields (Nani et al, 2023). This required efficient algorithms and scalable systems capable of handling large volumes of data with minimal latency. Research continues to explore new visualization techniques to effectively represent complex data including high dimensional and large datasets (Song, et al, 2022). This includes developing novel methods for data aggregation and creation of interactive and explorable visualisation.

**Creative Collaboration**

Computer-mediated environments (CME) are essential for innovation and the development of new ideas that contribute to the concept of creative collaboration (Chaffey, 2016). CME environments enhance creative tasks such as visualisation that implicitly improve collaboration through digital means (Backonja et al., 2018). This virtual space encourages feedback, interactions between artist and audiences with the presence of virtual artifacts (Pekka, 2015). Creative collaboration extends beyond direct human engagement, involves multiple interactions across different mediums (Barrett et al., 2021). The implementation of choreographed activities, aesthetics, playfulness and participation helps to create a space for collaboration (Calvo, 2021). The inclusion of cultural diversity and values with informal mutual learning are the key elements of effective collaboration. The modern way of living is directly linked with contemporary values, aspirations and creating meaning such as visualizing the lived experience of healthcare. (Kim et al., 2023).

The integration of data visualization and creative collaboration provides a rich space for the exploration of new forms of artistic expression. Data can be considered as an artifact within this process by transforming raw information into creative visual representation that communicates both information and emotions (Kim et al, 2022). This process enables artists to engage audiences in new ways, evoke emotions and inspire new spectate through data-driven processes (Rombach, 2020). The combination of artistic innovation with data sets allowed for public engagement and pushed the boundaries of traditional art. However, the interpretation of the abstract data visuals remains a challenge and requires the presence of supporting

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information (Andry et al., 2021). Data visualization must create meaning, and not just make data sensible, as visualised in bipolar disorder and in healthcare (Kim et al., 2023). The goal of data visualization in the creative context is to bridge the gap between data and the audience by evoking visceral and emotional response. This involves moving beyond conventional data representations and focusing on affective, meaningful and emotional value of data (Barrett et al., 2021). Data visualisation aims to evoke intuitive feelings within the user to support the understanding process. The real-time interactions, generative art can enhance data visualization, making it more engaging and accessible to a wider audience (Grba, 2021). This approach uses personal data as a source of self- reflection, promoting a better understanding of the user's emotional states.

## Methodology

The methodology for this research is based on a qualitative approach focusing on creative collaboration models by incorporating generative art, affective data in a computer-mediated environment (CME). The research aims to explore the potential of generative art in capturing the complexity of emotions and its effectiveness as a data visualization method. The grounded theory approach is used to study the relationship between brainwave data, generative art and emotional experiences.

Participants were recruited from the Kuala Lumpur region through online platforms, targeting young adults aged 25-34 with experience and interests in creative collaboration in the digital environment. The challenges faced during this process is digital literacy among participants especially in the area of generative art and data visualisation. This age group represents a significant portion of the Malaysian population and is likely to be familiar with digital media (Kemp, 2023). In this study, data saturation has been reached with 11 participants which shows different levels of intensity for both enjoyment and sadness. The sample size ranged from 10 to 50 participants, aligning with the guidelines for qualitative research, with the data collection process continuing until data saturation is reached (Creswell, 2018).

Participants engaged in a self-tracking process using electronic devices to generate visualisation of their emotions. A consent form is reviewed and signed by the participant before the data collection process. Data collection involved the following steps, textual stimuli, emotion questionnaires, EEG data collection, and data processing. The processed data is parsed through a node-based programming platform called TouchDesigner for the classification and visualisation process. Textual stimuli is used for the participants to recall impactful life events to evoke authentic emotions. This method was chosen over visual stimuli because textual dominates the meaning and elicits fixed and factual responses (Page et al., 2022).

Multidimensional Emotion Questionnaire (MEQ) is the next stage after the memory recall session. MEQ is used to assess both discrete emotions such as happiness and sadness and broad dimensions of reactivity in the area of positive and negative affect. The time duration is also being considered for the emotional experience. MEQ captures the frequency, intensity, duration and regulation of emotions which gives a detailed understanding of emotional response (Wilkins et al., 2024; Vives, 2020; Klonsky, 2019). The sample questionnaire was adapted from Klonsky (2019). This information was used to validate the authenticity of the generated visualization. Other instruments for assessing emotions such as Brief Mood Introspection (BMIS), Self-Assessment Manikin (SAM), Profile of Mood States (POMS), and Multiple Affect Adjective Checklist (MAACL) were also considered.

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The participants' brainwave data were collected using a Muse 2 headband, a consumer-grade EEG device with dry electrodes that provides insights into brain activity. The raw brainwave data that is being collected anonymously to protect the privacy of participants. The data were preprocessed and then parsed into Mind Monitor, a mobile application. The application specifically focuses on the preprocessing, selection and classification of the brainwaves (Craik et al., 2019).

The processed EEG data is streamed into TouchDesigner, a node-based platform used for generative visualization. In TouchDesigner, the brainwaves were classified using mathematical channel operators (MATH CHOPS) into different wavelengths such as Alpha, Beta, Delta, Theta and Gamma). Each wavelength is linked to specific parameters to control the visual reactions. The visual output was based on a torus shape to capture raw data without noise removal. The torus shape is preferred because the polygon count is significantly higher than a sphere. The density allows brainwaves to be mapped on a larger surface and scale. The visualizations were built using color mappings derived from Synesketch, an open source platform for textual emotion recognition (Krcadinac et al., 2013).

The creative collaboration model is used that involves interaction between participants with the generative system in a CME environment. Data collected from this interaction served as the basis for generating real-time visuals with the goal to project each participant's emotional state. Key aspect of this research was to capture and visualize noise data rather than removing it, to avoid losing relevant information. The findings from this research were presented in a geospatial augmented reality (AR) platform, which allows participants to interact with their emotion-based visuals on the devices. This AR experience provides a tangible and permanent connection between specific locations and the motions recalled by each participant. This allows the participants to revisit and reflect on their emotional data which is part of the objective of promoting self-reflection, human development and digital well-being.

## Findings

This research investigated the capacity of affective generative art, specifically the system termed "A-GEN01," to visualize and represent human emotions in real-time, within a creative collaboration framework, visualised in Figure 3.

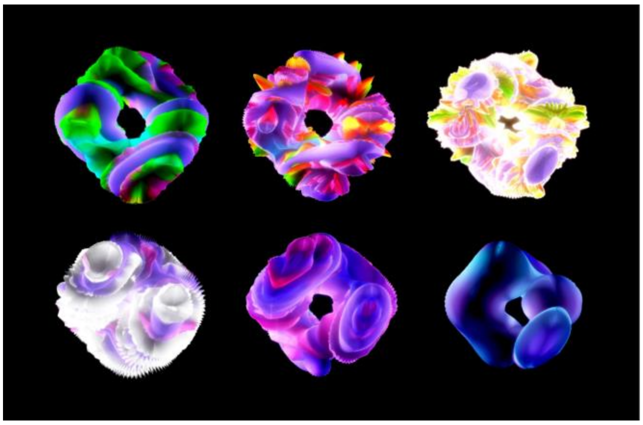

**Figure 3: AGEN-01 Generative Art**

### *Classification of Emotions*

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The findings demonstrate that A-GEN01 successfully captured the contrast between two broad emotional categories – enjoyment and sadness – based on participants' brainwave data and self-reported experiences. Furthermore, the research provides insights into the potential of such systems for promoting self-awareness and reflection on emotional states, with implications for digital well-being.

### *Visual Mapping*

This visual difference is evident across multiple visual parameters, including hue, saturation, texture intensity, and texture multiplication, as mapped to specific brainwave frequencies (Gamma, Beta, Alpha, Theta) via TouchDesigner shown in Figure 4.

| **Waves** | **Ranges** | **Mental States** | **Parameters** |
|---|---|---|---|
| Gamma | 30-100Hz | High Mental Activity and Concentration | Hue Offset |
| Beta | 16-20Hz | Thinking and Consciousness | Texture Intensity |
| Alpha | 8-12Hz | Reflective and Awareness | Saturation and Brightness |
| Theta | 4-7Hz | Remembrance | Texture Multiplier |
| Delta | < 4Hz | Deep Sleep and Unconsciousness | NA |

**Figure 4: Brain Waves, Range and Parameters for Visualisation.**

As detailed in Figure 5, enjoyment, particularly at "very high" intensity, was characterized by bright, yellowish hues, high texture intensity, and a rapid, dynamic motion. In contrast, "very high" intensity sadness is presented with saturated blue hues, lower texture intensity, and a slower, less dynamic motion. These visual distinctions were consistent across participants, suggesting a strong mapping between brainwave activity, emotional state, and visual output.

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| Emotion | Intensity | Visual Characteristics |
|---|---|---|
| Enjoyment | Very High | High paced motion, highly dense textured and multiplication, bright yellowish hue, consistent bright glow and slightly less saturated. |
| | High | Medium paced motion, mid range texture density and multiplication, purple-pink hue and saturated. |
| | Moderate | Medium paced motion, reduce texture density and multiplication, green and purple hue and saturated. |
| Sadness | Very High | Slowest paced motion, smoother texture and multiplication, bright blue hue, dark and highly saturated. |
| | High | Medium-paced motion, mid range texture density and multiplication, purple-bluish hue and saturated. |
| | Moderate | Medium-paced motion, highly textured, white-purpleish hue and very desaturated. |

**Figure 5: Mapping of Visual Characteristics to Emotions.**

### *Visual Summary*

The detailed range of visual outputs for this research are presented in Figure 6. The intensity of the emotions are classified into Moderate, High and Very High and the visual differences provide a distinctive outlook of the depth of emotions. Figure 7 and 8 showcased the summary of the visual intensity for both enjoyment and sadness.

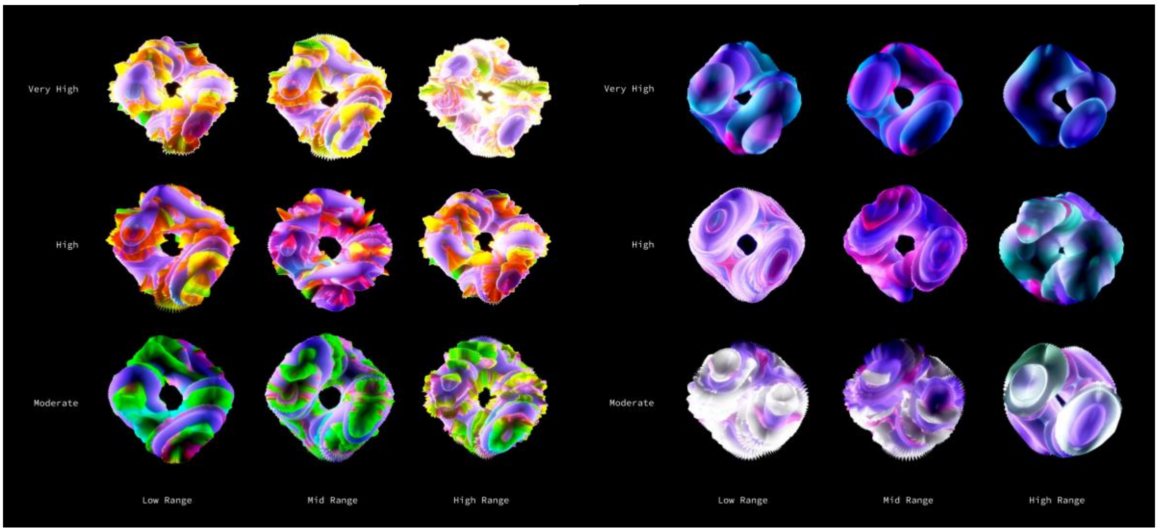


**Figure 6: Visual Range Characteristics**

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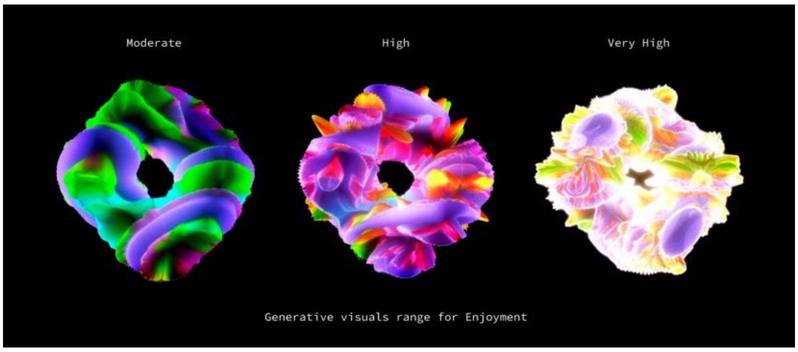


**Figure 7: Visual Intensity for Enjoyment**

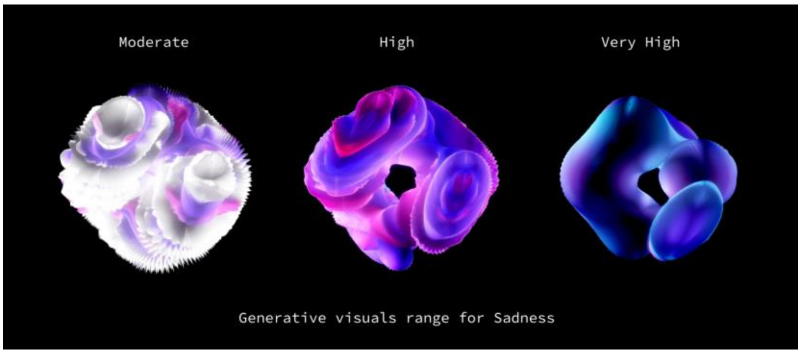


**Figure 8: Visual Intensity for Sadness**

***Color Palette Analysis***

The observed color palettes align with previous research on color-emotion associations. The dominant bright, saturated yellows and oranges in high-intensity enjoyment align with findings from Kushkin et al. (2023) and Krcadinac et al. (2016), who linked such colors to positive emotions like happiness and joy. The darker, more saturated blues associated with high-intensity sadness corroborate the association of such hues with negative emotions, as documented in Figure 9.

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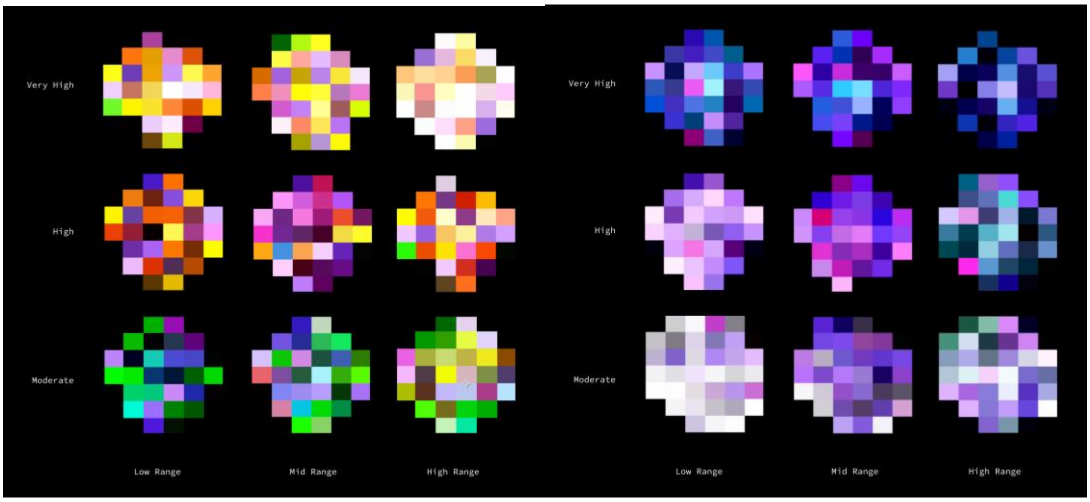


**Figure 9: Color Palette Range for Enjoyment and Sadness**

***Brainwave Data***

Analysis of the average brainwave readings during the data collection sessions revealed distinct patterns for enjoyment and sadness. Enjoyment was associated with higher overall power across different wavelengths, particularly Gamma and Beta, suggesting increased cognitive activity and alertness (Diaz, 2021). Sadness, while showing higher Alpha activity in the "very high" category, potentially indicating a state of reflection or withdrawal, generally showcased lower power across other frequencies. This supports the notion that A-GEN01 is capturing genuine physiological links of emotional states.

***Participant Experiences and Self-Reflection***

The qualitative data gathered through the Multidimensional Emotion Questionnaire (MEQ) (Klonsky, 2019) and post-session discussions provided valuable insights into participants' experiences with A-GEN01. Figure 10 shows that 54.5% of participants chose Enjoyment and 45.5% chose sadness. Figure 11 illustrates the recency bias, with the majority of recalled events occurring within the past year. Overall, both enjoyment and sadness events are recalled within the 1-year range.

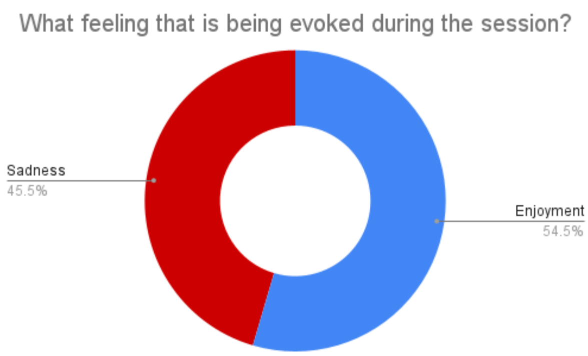


**Figure 10: Groups of Emotion.**

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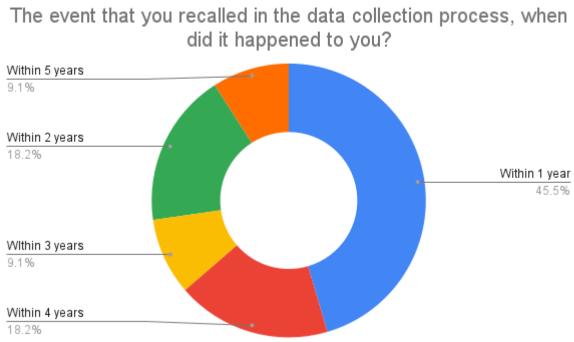


**Figure 11: Overall Timeline Events.**

***Participants Feedback***
A consistent theme across participant responses was the perceived benefit of visualizing their emotions. Participants reported that the real-time visual feedback provided clarity and a deeper understanding of their emotional states during the recall of significant life events. Statements such as "it gives a more in-depth data on how emotions occur" (Participant 7) and "it can allow us to understand and identify things that sometime we might overlook" (Participant 6) highlight this enhanced self-awareness.

The data revealed participants tend to recall more recent events, particularly for enjoyment. This aligns with the concept of recency bias, where more recent memories are more accessible (Kalm et al., 2018). While this bias is a factor, it does not influence the validity of the emotional responses, as the generative visuals accurately reflect the reported intensity and duration of the recalled emotions.

The MEQ data shows that enjoyment experiences were generally reported as more frequent but of shorter duration (typically 1-10 minutes), while sadness experiences were less frequent but could last longer (up to 1-4 hours). This difference further underscores the nuanced emotional representation captured by A-GEN01.

**Discussion**
This research was framed by the three primary research questions.

***Research Question 1: Can Generative Art Capture The Complexity Of Represented Data?***
The findings of this study provided evidence that generative art, specifically the A-GEN01 system, can effectively capture the complexity of the represented data referring to human emotional states.

As showcased in Figure 3, A-GEN01 successfully differentiated between enjoyment and sadness based on distinct visual characteristics from the real-time EEG data source. These characteristics include variations in hue, saturation, texture intensity, texture multiplication and motion. Each mapped to specific brainwave frequencies as reflected in Figure 4.

The ability to visually distinguish between different intensities of emotion starting from moderate, high to very high further demonstrates the system's capacity in capturing the depth

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of emotional experience. The correlation between color palettes and emotional states alight with existing research on color-emotion associations (Kushkin et al., 2023; Krcadinac et al., 2016). This provides further validation on the system's ability to represent emotional data meaningfully.

The system captured the dynamic nature of emotions, with variations in visual parameters reflecting changes in brainwave activity over time. The real-time visuals is a significant advantage over static data visualization.

***Research Question 2: How Can We Develop Generative Art As A Data Visualization Method For Capturing Human Emotions?***

This research provides a concrete example on how generative art can be developed as a data visualization method for capturing human emotions. This demonstrates a valid methodology and outlining key design considerations.

The development of A-GEN01 involved multiple stages of processing, beginning with selection of a consumer-grade EEG device, Muse 2 headband and a real-time data processing platform which is TouchDesigner. A key step that contributes to the methodology is the mapping of specific brainwave frequencies (Alpha, Delta, Beta, Theta and Gamma) to visual parameters within TouchDesigner as reflected in Figure 4. The mapping is supported by existing literature on brainwave activity and emotional states (Diaz, 2021).

The choice of torus as the base geometry is supported by its higher polygon count compared to a sphere, allowing for a mode-detailed representation of the brainwave and data noise. The creative collaboration framework focuses on the interaction and feedback between human and system supports the idea of generating visuals that are meaningful and relevant to the participants emotional experiences. The usage of textual stimuli to evoke emotion with MEQ as validation method for the brainwave data.

***Research Question 3: How Effective Is Generative Art In Creating A Meaningful Representation Of Personal Data?***

The findings indicated that A-GEN01 was highly effective in creating meaningful representation of participants' personal emotional data, encouraging the idea of self-reflection and enhancing emotional awareness. The qualitative data gathered through the MEQ and post-session discussion consistently highlighted the perceived benefits of visualizing emotions in real-time.

Participants reported that the system provided clarity, helped them to understand their emotions better, and allowed them to identify aspects of their experiences they might have otherwise overlooked. Statements such as "it gives a more in-depth data on how emotions occur" (Participant 7) and "it can allow us to understand and identify things that sometime we might overlook" (Participant 6) highlight this enhanced self-awareness. The positive feedback from participants, coupled with the objective of classifying emotions through visual characteristics, strongly suggest that the A-GEN01 was effective in creating meaningful representations.

In summary, this research has demonstrated and answered its guiding questions. This has shown that generative art can capture the complexity of emotional data, provided a concrete methodology for developing such a system and confirmed the effectiveness of this approach in creating meaningful and personal relevant visualizations. These findings contribute significantly to the understanding of how technology can be used to visualize and interact with human emotions, with evidence from fields such as affective computing, data visualisation and digital well-being.

**Conclusion**
Findings managed to address the objectives of this study, which showed that generative art can capture complex emotions, worked effectively as a data visualisation method and created meaningful data representation. The visual representation of emotions, A-GEN01 and similar systems can help individuals develop a greater understanding of their own emotional data and classify different emotional experiences. This enhanced emotional literacy is crucial in the area of emotional intelligence and overall well-being in the digital landscape.

The real-time feedback provided by the system can empower individuals and to become more aware of their emotional responses. This allows individuals to develop plans to manage and regulate their emotions more effectively. This is particularly relevant in the area of stress management, anxiety and overall mental-health.

A-GEN01 system responds in real-time and changes dynamically is a plus in assisting participants reflect and understand their emotions. The system proves that humans and machines can collaborate for humanistic goals such as increasing self-awareness and emotional well-being. The unique and personalized system of the generated visuals offers potential for individuals to gain insights of their own emotional data patterns. This will lead to a greater self-knowledge and growth towards better personal space.

Acknowledging the sense-making of generative art and getting visibility from the general public remains a challenge. Further research is needed for the system to be adapted into the use of the therapeutic environment, as a tool for emotional expression, exploration and processing. This could be beneficial for individuals who struggle to verbalize their emotions. The ability to visualize and understand emotions in real-time can contribute to a more positive and mindful engagement with technology. In essence, affective generative art offers an opportunity to bridge the gap between human emotions and the digital world, promoting a harmonious and insightful relationship between human and technology.

**Limitations and Future Directions**
This research produced promising results, it's important to acknowledge its limitations, especially on the focus of only 2 extreme ranges which is enjoyment and sadness, the self-reporting data and small sample size. Future research could explore a wider range of emotions, incorporating additional physiological measures, and investigate the long term effects of such systems. Further development could also explore the integration of artificial intelligence to enhance the generative visuals.

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