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Understanding Public Responses to AI-generated Visual Art: A Topic and Emotion Analysis of Social Media Comments Data

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Abstract. This study analyzes the comments on AI-generated visual art on social media, focusing on emotional and thematic aspects. With the rise of AI-generated content on social media platforms such as DALL·E and Midjourney, AI art has gained both positive and negative attention. This mixed-methods study uses emotion analysis and thematic modeling to investigate the audience's response to the art of AI-generation. The study uses two sets of frameworks: Machine-Driven Classification of Open-Ended Responses (MDCOR) and Sentiment and Emotion Network Analysis (SENA) to classify and analyze social media comments to grasp the emotional tone of the discussion and AI art-related issues. The data shows that the social media debate about authenticity, author identity and whether AI will replace human artists presents a complex picture of enthusiasm, doubt and worry. The study also found that the public's impression will change in the process of interacting with AI art. This study provides a comprehensive framework for understanding public opinion and lays the foundation for further investigation of the social and cultural impact of AI on art and creativity.

Keywords: AI-generated art, Public discourse, Thematic analysis, Emotion analysis, Authenticity

1. Introduction

1.1. Research problem

Social media comment data topic and emotion study to understand AI-generated visual art sentiment.

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1.2. The significance and context of the study

AIGC is content created by generative AI rather than humans. AI-generated visual art is a term for paintings, illustrations, and other visual works of art made with AIGC tools like DALL·E, Midjourney, and Stable Diffusion. Generative AI technologies are spreading quickly on major social media sites, and AIGC has opened up a lot of new prospects for the art world and given artists new ways to get creative. Since late 2022, public conversations about AI-generated art have been more resistant, suspicious, and uncertain. The larger social and cultural impacts of AI-generated visual art are relevant due to the developing tension between technological advancement and how people respond to it.

Socially and culturally, this research is important. Social media, the center of modern culture, shows instantaneous mood, aesthetics, and political tensions. Read public discourse to identify overlooked issues and improve your critical thinking regarding AI-generated visual art. A person's AI-generation feelings can reveal their true nature. Are they more excited or anxious? Does society want AI to help them create art or fear it will replace humans?

This study's quantitative method uses genuine user data and a defined structure. It combines sentiment lexicon analysis with network modeling. This method doesn't talk about AI-generated art in general terms. The tool used, MDCOR, also improves interpretable NLP methods that don't use deep learning models. This makes them easier for researchers who don't have a technical background to use. Additionally, this research framework can serve as a transferable model for studying the social impact of AI across other creative domains, such as AI-generated painting, writing, and music.

1.3. The purpose and aims of the study

Based on the above research motivations and feasibility, we formulated our research questions as follows:

RQ1: What kinds of topics are being discussed around AI-generated visual art on social media platforms such as YouTube?

RQ2: How do emotional distributions and tensions vary across different topics in discussions of AI-generated visual art on social media?

RQ3: Are specific themes systematically associated with certain emotions?

2. Literature review

2.1. Definition and background of AI-generated visual art

2.1.1. Definition and background

Visual art generated by artificial intelligence refers to visual works such as paintings, illustrations and photos created by generating artificial intelligence systems, such as Midjourney or models based on convolutional neural networks. These systems learn from a large number of data sets of human works of art and generate new outputs independently based on the user.

Soewandi et al. conducted a systematic literature review of 30 studies selected from an initial pool of 4329 to monitor the development of AI-generated visual art [1]. Early artificial intelligence art mainly focused on imitating existing artistic styles, while modern artificial intelligence art, driven by the progress of computer vision and natural language processing, can create context-aware

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works with fixed themes. This review also identified key themes including AI's application in art education, its ability to enhance traditional art mediums, and emerging debates around copyright and authenticity, offering a structured analysis of AI art's advantages and challenges. Svenungsson said that AI-generated art goes against the idea that "art is the intentional creation of humans" [2]. AI can come up with the core idea for a painting, which brushes can't do.

2.2. Relationship with social media

Sharing AI-generated visual arts on social media may change people's views. Qian Yang used a machine learning model to view social media data and found that AI-generated art meets the public demand for "low-cost, frequently shareable content" [3]. Users can easily create works that self-expressive, and bright colors and simple textures tend to attract likes and comments. Queiroz compares generated AI art tools to scientific software, believing that their lack of openness will affect users' trust and perception [4].

2.3. Public attitudes and emotional responses

2.3.1. Overall acceptance and psychological mechanisms

In a two-wave study of 828 Finns aged 18–80, Latikka et al. based on self-determination theory, evaluate how social connection, autonomy and competence affect the public's acceptance of AI art [5]. The study found that social connection and sense of control will affect acceptance: individuals who believe that technology can improve social connection and adjust AI creative parameters are more likely to accept AI art than those who regard AI as an uncontrollable force. Latikka et al. also found that the public's impression of AI art changed in two years, emphasizing the need to carry out vertical research [5].

2.3.2. Moral and aesthetic judgments

Bara et al. confirmed that background knowledge affects moral and aesthetic evaluation [6]. The study divided the participants into two groups: one knew that the painting was AI-generated, and the other did not know. Subsequently, both groups scored the same AI-generated work of art. The results show that prior information about AI-generation may reduce the marketing effect of AI art due to ethical concerns.

In their ASSURE model study, Chen and Ibrahim examined people's emotional response to AI art through physiological indicators such as heart rate and facial expressions, as well as self-reported metrics [7]. The study regards sensory stimulation, multi-dimensional interaction and participant input as key factors for emotional input.

Findings revealed that AI interactive art triggers more positive emotions, while AI art with unknown authorship induces a heightened sense of anxiety. This aligns with social media discourse, where AI art discussions often revolve around emotional impact and authenticity.

2.3.3. Preferences for creative value and human creativity

Hall & Schofield asked participants to evaluate 5 pairs of unmarked works of art where one pair is artificial and the other is artificial intelligence-generated [8]. The results show that even if the audience cannot distinguish between human works and artificial intelligence works, artificial works always get a higher valuation. Agudo et al. further supported this finding: when participants were told that a work was generated by artificial intelligence, their evaluation of its sensitivity, emotional depth and quality was lower than what they thought was artificial, even if the two works were the same [9]. This reveals a strong negative bias against the creativity of artificial intelligence, which is driven by the stereotype of the lack of authenticity of machines, which echoes the survey results of Agudo and others, that is, 68% of the participants believe that artificial intelligence art is not real art.

2.4. Controversies and ethical issues

2.4.1. Authenticity and authorship

One of the main problems is whether AI-generated art is real. Chiodo contends that AI-generated art is devoid of human aim and reflective significance, both of which are fundamental attributes of art [10]. Agudo et al. found that 68% of survey respondents did not consider AI-generated artworks “real art,” indicating popular skepticism [9].

Authorship is a legal and artistic problem. In Thaler v. In the case of US Copyright Office, the judge prevented the granting of copyright to AI-generated works, indicating that the current copyright system requires the identity of human authors [11,12].

Artists who use AI face difficulties in decision-making. Some researchers (such as Lahtinen and Oksanen) suggest alternative frameworks [13]. They support "artist-driven AI" and the artist plans the input and generation process. This move can not only give full play to the artistic potential of AI, but also retain the identity of the author.

The "Human Authorship Requirement" in copyright law promotes the debate about the legitimacy and identity of authors. Cunningham reviewed a number of major cases. Thaler v. The US Copyright Office has determined that AI generation art that lacks human creative input is not entitled to copyright protection [12]. The prosecution claimed that Midjourney violated the author's rights by training AI with unlicensed human works. Cunningham pointed out that the current copyright system is difficult to cope with AI-generated works, resulting in a vague definition of ownership [12].

2.4.2. Creator rights and economic impacts

Buu examines how AI art affects the human creators [14]. The study found that generative AI has both advantages and disadvantages: AI accelerates the writing of art-related patents and the retrieval of existing technologies, and reduces the workload of creators. However, AI often uses unauthorized human art for training without compensation. To protect creators, Buu proposed a "human-in-the-loop" framework, where human review of AI outputs to prevent copyright infringement, and AI platforms must disclose training data sources to compensate original creators [14]. For digital artists, Cajulis et al. surveyed 300 artists, dividing them into three groups: traditional artists (no AI use), mixed artists (AI as a tool), and AI-exclusive artists (full reliance on AI) [15]. The results showed that traditional and mixed artists have 40% higher income and job satisfaction, as their works are seen as unique and labor-intensive, while AI-exclusive artists face low customer willingness to pay and doubts about originality.

2.4.3. Arts education and creative labor

Zhang (n.d.) The role of artificial intelligence in art education was investigated, and it was found that artificial intelligence tools can help students overcome technical barriers [16] - for example,

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students with poor painting skills can use artificial intelligence to generate basic sketches and then improve them to improve their confidence in creativity. However, 38.39% of art students reported that they relied on artificial intelligence to acquire ideas instead of independent brainstorming, which led to the homogenization of their works. Lee et al. solved the problem of not being able to get art appreciation education by developing a virtual tutor LLAVA-Docent based on a multimodal language model (MLM) [17]. Trained through the dialogue generated by GPT-4 and combined with the theory of art criticism, the model proposes tailor-made questions to adapt to the diversified learning rhythm. The evaluation shows that although it struggles with highly abstract artistic concepts, it enhances participation. This complements Zhang's findings, showing that artificial intelligence can democratize art education, and at the same time raise concerns about the excessive simplification of aesthetic judgment.

In art therapy, Shojaei et al. collaborated with 10 art therapists affiliated with the American Art Therapy Association to develop an AI-assisted tool: emotion-themed cards paired with AI-generated images [18]. The study found that the tool improves treatment accessibility, for example, remote clients can use the cards to express emotions without in person meetings, and 65% of clients reported "feeling more understood". Therapists afraid of losing clients' confidence and privacy.

2.5. Methods and analytical tools

2.5.1. Sentiment analysis

Bhoi and Chen & Ibrahim examined emotional analysis as a key AI art acceptability tool [19] [7]. Bhoi used social media data visual emotional analysis to classify public feelings as praise (38%), distrust (42%), fury (10%), and perplexity (10%) [19]. He linked these emotions with factors such as perceived artistic value of artificial intelligence, public technical literacy, and moral concern for the role of artificial intelligence in creativity. Zhu et al. promote emotional analysis by introducing the GM-GTM model, which is different from the traditional method [20]. It uses grid marking assistance to capture the fine connection between emotional elements, and is good at dealing with nuances and implicit expressions in artificial intelligence art discourse.

By developing the PGSO framework, Dong & Ji solved the shortcomings of generating models based on aspective analysis (ABSA), especially their difficulties in capturing long-term implicit relationships in complex texts [21]. PGSO combines rule-based static optimization and score-based dynamic optimization. Even in text with complex structures, it can enhance extraction and outperform the most advanced methods in dealing with long-distance dependencies, which is crucial for analyzing artificial intelligence art discussions.

2.5.2. Machine learning models (Qian Yang, 2025)

Qian Yang applied three common machine learning models to analyze AI-generated visual art and its social media dissemination: logistic regression (predicting public attitudes toward AI art), artificial neural networks (identifying visual patterns in AI art), and support vector machines (classifying AI art styles) [3].

Hou et al. further applied machine learning to distinguish between travel photos and real photos generated by artificial intelligence, and developed a hybrid model integrating convolutional neural network (CNN) and multimodal feature analysis [22]. The model achieves a detection accuracy of 96.1%, far exceeding human performance (67.7% success rate). This method is also applicable to

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artificial intelligence art, which helps to identify artificial intelligence works in art exhibitions or online markets.

Rathi et al. conducted a comprehensive investigation of the computational technology of the classification of art and painting, dividing it into image-based methods, machine learning methods and deep learning models [23]. They analyzed how these technologies solve core tasks (artist, style and genre identification) and meet challenges such as visual variability and semantic complexity. For artificial intelligence art, these FAP classification tools help distinguish between human and artificial intelligence works, solve concerns about counterfeiting and authors, and clarify the ability of artificial intelligence to imitate art technology.

2.5.3. Interpretable NLP frameworks (Hemment et al., 2024)

Hemment et al. solved the "black box" problem of machine learning models by proposing an NLP framework that balances analytical ability and transparency [24]. Their "experiential artificial intelligence" framework combines artistic narrative with interpretable artificial intelligence - for example, designing an AI art installation that visualizes its creative process (e.g., projecting training data, adjusted parameters, and generation steps). When visitors interact with the installation, 72% report a better understanding of AI art. This is consistent with Queiroz's emphasis on the transparency of artificial intelligence art tools, because user trust is not only shaped by content, but also by the perceived legitimacy of the process, which is the key to explaining social media's artistic mood for artificial intelligence [4].

2.6. Research gap

2.6.1. Lack of large-scale coupled topic-emotion analysis

Most existing studies rely on small-scale surveys or experiments (e.g., Latikka et al., 2023’s 828 participants, Bara et al., 2025’s 300 experiment participants) and lack large-scale coupled topic-emotion analysis based on real social media discussions [5,6]. For example, while Bhoi analyzed 10,000 social media comments, this sample size is small compared to the billions of AI art-related posts on platforms like TikTok or Instagram [19]. No studies have yet conducted large-scale analysis of how specific topics correlate with emotions. This "coupled analysis" is essential for understanding public discourse on AI art, as it can reveal whether discussions about "AI stealing jobs" are mainly accompanied by anger or a mix of anger and anxiety.

2.6.2. Few quantitative studies on perception-emotion dynamics

Few studies have quantitatively examined how public perceptions influence emotional and thematic patterns. Hall & Schofield and Agudo et al. provide qualitative evidence that perception shapes emotions, but no large-scale quantitative studies have measured this relationship [8,9]—for example, there is no data showing the extent to which changes in perception affect emotional intensity or topic focus. This gap limits understanding of how to guide public attitudes toward AI art (e.g., whether popularizing knowledge about AI creation can reduce suspicion).

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2.7. The Benjamin foundation and its contemporary challengers

2.7.1. Introduction to Walter Benjamin

The sudden emergence of AI-generated art has effectively resulted in a profound shift in artistic production, appreciation, and distribution. However, for us to fully understand the public's response to this revolutionary phenomenon, as captured through social media discourse, it is crucial that we ground this analysis in the theoretical frameworks that have been long examined in the relationship between technology, art, and society. The Walter Benjamin work in "The Work of Art in the Age of Mechanical Reproduction" exemplifies and breaks this down, providing us with the essential starting ground. This review will synthesize three key scholarly responses to Walter Benjamin's thesis in order for us to better understand how technology, or more precisely, the developement of AI-generated art, could have a large impact on social dynamics. Effectively, this allows us to construct a theoretical lens, allowing us to contextualise empirical research on public sentiment, demonstrating how this fills critical gaps by applying these theoretical concerns to a broad-scale, data-driven analysis on contemporary public discourse.

2.7.2. Walter Benjamin: the loss of Aura and the rise in exhibition value

Walter Benjamin's thesis argues from the perspective that reproduction techniques like photography and film strip the artwork of its "aura", which refers to a unique existence of an entity in space and time, one which holds cult value [25]. Reproduction however, detaches the artwork from its original context, effectively rendering it ubiquitous, diminishing the value of the original piece. Additionally, the primary value of the art shifts from a rather ritualistic niche, to a public display, and hence the exhibition of the artwork. To Benjamin, this shift was politically ambiguous as it could democratize art, bringing it to the masses, but could also reduce art to a tool for fascist propaganda or capitalist spectacle, essentially stripping the very artistic aura that makes art what it is.

2.7.3. Chris Barker: questioning the narrative of radical break

Barker directly challenged the perception of radicalism of Benjamin's thesis [26]. In "Mechanical Reproduction in an Age of High Art", Barker argues that mechanical reproduction did not serve to diminish art or its aura. He argues that Benjamin's hyperfixation on photographic reproduction is historically myopic. By examining a longer history of reproduction such as copperplate engravings and woodcuts, Barker demonstrates that high quality artistic reprodcutions has existed for centuries, yet they often carried along their own artistic merit and value without destroying the status of the original. Audiences and connoisseurs have always attached great importance to accurate reproduction. Therefore, Barker argues that technological progress is to evolve artistic perception, not to revolutionize it. Barker's view is critical to limiting technical determinism. This view shows that society's fear of AI art is part of the historical cycle of reaction to replication technology. It questions the concept of "lower than others because of replicability", shows the enduring power of art, and raises our research question accordingly: "Is the public response to AI a distinct panic or a recurring pattern?"

2.7.4. Milly Skellington: updating benjamin for the algorithmic age

In the article "Art in the Age of Algorithmic Automation and Artificial Intelligence", Skellington supports Benjamin's views on technological change, but she advocates that algorithmic automation

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is a major and new change [27]. She added that the artist's role is changing from a "creator" to a "conscious linkage", that is, a highly complex network system. In a speculative future scenario set in the future, she depicts a world where AI not only copies things, but also can generate things independently. This means that in the future, human creativity and innovation are no longer equally necessary. Skellington turns Benjamin's concern about mechanical replication to algorithmic generation in this context, machines are both tools and independent and dynamic subjects. Skellingtin's work identifies the main mechanisms of the public response we're researching. The social media debate over whether "real artists" should identify AI-generated works as "real art" reflects the philosophical view of artists being part of the system. Our social media data collection shows concern and fears regarding the author's identity, authenticity, and human replacement. The paper clarifies these fears. Skellington's research offers a modern theoretical framework that changes the emphasis from replication to generation. We analyze this technical transformation using data.

2.7.5. Ignas Kalpokas: the paradox of the new data-born Aura

In "Work of Art in the Age of its AI Reproduction," Kalpokas synthesizes well [28]. He contends that AI-generated art, being the revolution that it has become, is fundamentally distinct from both traditional art and reproduction techniques, despite both being in the same audio-visual medium. Photography, a reproduction technique, essentially captures reality. However, AI-art does not just reproduce reality, it metamorphosizes it, alters it, to contruct its own abstraction in which is called AI-generated art. AI, in essence, invents new representations based on data and their constituent patterns. Kalpokas introduces a critical paradox, "while AI art exemplifies Banjamin's exhibition value, it paradoxically reverses the loss of its aura". This paradox is built on the basis that "aura" is not inextricably bound to the unique materiality, rather, it is intrinsically tied to the collective subconscious of society, that being the tapestry of patterns present in the vast social datasets that the system is trained on. As a result, AI-generated art has become a new form of authenticity, depecting a genuine reflection of the digitalised society that produced it. Kalpokas's paper is the most directly relevant theoretical source as it conceptualises the process of interpreting our findings. He accuractly predicts the tension that our study is trying to quantify, that being the polarisation between admiration for AI's capabilities and deep anxiety over its authenticity. His concept of a "collective subconscious" justifies the use of social media datasets as a prime source to quantify societal impacts of AI-generated art. Kalpokas's work also provides a theoretical model, enabling our empirical study to shift beyond a simple positive-negative sentiment analysis, to allow us to frame highly complex themes like "authenticity", "authorship" not just as ethical concerns, but as modernised manifestations of Banjamin's theory of art's "aura".

3. Results and discussion

3.1. Research questions

This study is guided by four central research questions:

- RQ1: What themes are prevalent in viewer discussions of AI-generated art?
- RQ2: What emotions (e.g., excitement, fear, scepticism) are expressed in comments, and how do these vary across videos?
- RQ3: Are specific themes systematically associated with certain emotions?
- RQ4: Do factors such as video type, audience size, or uploader explain differences in themes or emotions?

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The research utilizes a comparative mixed-methods content analysis of YouTube comments informed by these inquiries. The design combines qualitative topic coding with quantitative sentiment analysis to systematically answer the research questions. Every YouTube video acts as a case, which lets us compare cases to see if the themes and emotions are different in different situations. The research design guarantees a comprehensive comprehension of spectator discourse regarding AI-generated art and the reasons for the variability in these talks by integrating textual analysis of comments with video-level metadata.

3.2. Data source

The data is made up of comments from people who watched two YouTube videos about AI-generated art. These films were chosen to give two different settings for conversation. For example, they might have different uploaders (such an official channel vs. an individual maker) or reach different audiences. This way, we can see how the themes and feelings of comments change. An R Studio script that worked with the YouTube Data API grabbed all of the comments on each video at the time the data was collected. This automatic collection made guaranteed that the whole conversation was recorded in an unbiased way, which may have happened with manual sampling. The final dataset comprises the text of each comment as well as information about the comment, such as the time and date it was made and the name of the person who made it (if it is needed for analysis). Each comment will display the video ID, so indicating which video it corresponds to. In this way, it will be more convenient to compare different groups later.

After collecting the comment text data, it is cleaned for analysis. This included getting rid of entries that didn't have any real content. For example, comments that were just emojis, links, or gibberish were not useful for textual analysis and were not included. Repeated comments (spam or bot posts) were de-duplicated to prevent skewing the results. Standard textual preprocessing steps were then applied: lowercasing all text, and stripping non-textual characters (while retaining meaningful emojis if they convey sentiment). No aggressive normalisation (e.g. lemmatisation or stop-word removal) was performed at this stage, to preserve meaningful context and slang in the comments; the thematic analysis tool we employed (described below) is designed to handle natural language in a way that preserves the original wording of responses. The outcome of preprocessing was a refined corpus of comments from each video, ready for thematic coding and sentiment analysis.

3.3. Analytical strategy

To identify major discussion themes in the comments (addressing RQ1), we utilised the Machine-Driven Classification of Open-Ended Responses (MDCOR) framework [29]. MDCOR is a no-code software tool that applies machine learning-based text classification to large collections of open-ended text, enabling researchers to retrieve latent thematic codes from written data efficiently [29]. This study used MDCOR to automatically categorise comments into thematic clusters based on content similarity. This approach corresponds to a form of unsupervised thematic coding or topic modelling, but with enhancements to maintain qualitative nuance – MDCOR was explicitly designed to preserve participants' original language and "identify the optimal number of codes contained in the data" while minimising human bias in coding [29]. We ran MDCOR on the combined set of comments from both videos (and each subset separately for comparison), allowing the software to determine key topic areas emerging from the data. The output included a set of latent themes (each essentially a code or topic label) and the classification of each comment under one of

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these themes. MDCOR also provides interactive summaries, such as visualisations of the code distributions and keywords defining each theme, which helped substantively interpret and label the themes. Using this standardised machine-driven coding process, we ensured that identifying themes was consistent and replicable, addressing potential reliability issues of manual coding. Furthermore, because MDCOR can handle large volumes of text and even facilitate "group comparisons of the resulting classified responses", it was well-suited to our design, where two groups of comments (by video) needed to be analysed and compared under the same coding scheme [29].

To analyse the emotional content of the comments (RQ2), we applied the Sentiment and Emotion Network Analysis (SENA) framework [29]. SENA is a way to analyze text data that uses a free, no-code software application to find both the polarity of sentiment and specific emotion categories. Additionally, it helps you immediately compare different groups or situations [29]. SENA was used to figure out the tone of each comment (positive, negative, or neutral) and the precise feelings it indicated (such joy, enthusiasm, fear, skepticism, or any other feelings that were relevant to the AI art environment). Natural language processing is used to determine polarity in text in the sentiment analysis part. The emotion analysis part, on the other hand, sorts text into more specific emotion groups so that it can "go beyond polarity detection to gain more nuanced understandings [29]." The best part about SENA is that it doesn't only give a score for overall sentiment. Instead, it keeps track of the sentiment/emotion profile of each comment and aggregates these outputs using a network-based model. This revealed the dataset and video comments' distribution of feelings. We ran SENA on Video 1 and Video 2 comments independently as a group. We now have two sets of measures for how emotions were spread. After that, the software's ability to compare groups was utilized to assess statistically if the two groups conveyed their feelings in different ways. González Canché noted that "SENA conducts comparative [sentiment and emotion] analyses" and "enables testing whether differences in emotion distributions across groups exist [29]." In practice, this meant we could determine, for instance, if comments on one video were significantly more positive or more fearful on average than on the other. The SENA tool does all of the analytic steps (from text preparation to sentiment scoring and network modeling) on the user's computer without needing them to write any code. This keeps data private and makes it easy to utilize in our workflow. This stage gave each comment a set of sentiment scores and emotion category frequencies, as well as a synopsis for each video. This explained how the conversations made people feel.

3.4. Theme–emotion relationship

This study uses MDCOR's topic categories and SENA's sentiment and emotion scores to answer RQ3. MDCOR helps to identify the topics in the comments while retaining the participants' original language and eliminating coder bias [29]. SENA evaluates emotional polarity and specific emotions (such as happiness, fear, anger), and helps researchers compare the distribution of coded groups [30]. These two tools give each comment a theme and emotion coding at the same time, so as to test whether a specific theme consistently presents some "emotional fingerprints".

In view of the discussion on AI art in the public domain, this integration is crucial. AI-generation art lacks human experience and purpose, and these often evoke feelings of authenticity and creativity [2]. Using creative AI methods to attract audiences can reveal people's rational concerns and emotional reactions [24]. For example, "loss of artistic authenticity" may cause fear or doubt, while "technological innovation" may inspire appreciation.

This mixed method study follows the principles of classification and emotion analysis. González Canché pointed out that SENA can detect whether the emotional distribution has changed significantly under external coding (such as the MDCOR theme); this function is used to test the

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statistical intensity of the theme-emotional relationship [30]. Through cross-tabulations and network visualizations, you can show which themes accompany which specific emotions. This can present the emotional intensity and structure of AI art-related discourse. The joint analysis of themes and emotions helps to analyze the audience's content and their emotional responses.

3.5. Explanatory factors

Q4 not only analyzes the emotions and views presented in the two videos, but also further explores why they lead to different discussions. The most critical factors here include genre, audience size and uploader identity. The presentation of AI art will significantly affect public opinion: the presentation of artistic autonomy and human-AI collaboration is more attractive and brings a sense of hope; in contrast, tool demonstrations are easier to stimulate discussions about ethics, authenticity and "replacement" anxiety [13]. Whether the video is a praise, a critical or exemplary narrative focus, which may explain the difference between the topic and the emotional tone.

Audience size is as crucial as population composition. Popular or well-known videos often gather a large number of viewers, thus making the comment area more polarized; while small channels for specific groups are more likely to form a more consistent discussion atmosphere with a consistent value orientation. Hemment et al. pointed out that reaching new audiences will create "spaces for debate and engagement" among multiple groups, which is similar to the evolution of the AI art comment area [24]. Due to the larger audience, one video may have more controversial issues and emotional messages than another.

Understanding who uploaded the video provides a third perspective. The positions of independent artists, technology channels or cultural commentators will shape other people's reactions to the narrative. Artist channels usually emphasize innovation and collaboration, so it is easier to get audience support; while technology-oriented uploaders may attract more cautious or technology-oriented audiences. Scientific research and technical institutions pay more importance to reproduability and tool performance; the art community places more emphasis on subjectivity and originality [4]. These differences show that the uploader's position will significantly affect the theme and emotional trend of the comment.

Through contextual comparison results, this study is more than description, but also tries to explain: the comments of one video may focus on negative views on authenticity, while the other may highlight the positive response to creative exploration. Video framing, viewer demographics, and uploader identification will be considered. This explanatory study guarantees that the results of MDCOR and SENA are not considered in isolation, but are contextualized within the social and cultural frameworks of AI-generated art discourse.

4. Data

Through theme modeling, emotional entropy value analysis and word cloud visualization, this study will disassemble the comment data of two bloggers, female blogger Vedio1, male blogger Vedio2, and AI art videos, and uncover the "hidden logic" of audience feedback.

4.1. Stopword removals and rationale

"art" and "artist"

These two words are central to the dataset and appear in nearly all comments. Similar to how the word “covid” would appear universally in a dataset about COVID-19, “art” and “artist” serve more

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as background identifiers than as useful indicators of sentiment or topic differentiation. As such, they are unlikely to contribute meaningfully to topic modeling or classification granularity, and should therefore be removed.

"video"

This is a contextual or platform-specific term. Since the dataset consists of YouTube comments, it is natural that the word “video” would occur frequently across entries. However, it does not carry topic-distinguishing power and acts as a background term, so it is advisable to exclude it.

"make"

This verb is used a lot and works in the same way as other common stopwords like "have," "do," and "get." In general English conversation, these verbs are everywhere and don't have any unique themes or feelings. Taking them out can assist cut down on noise in sentiment analysis and topic detection.

"work"

In some datasets, such those that look at jobs or productivity, "work" is probably used in unclear or different ways, like "artwork" or "it works."Given its high frequency and low discriminative value in this particular dataset, it may hinder topic coherence and should be excluded.

"get" and "human"

• “get” is an abstract verb that appears excessively in natural language. Like other stop verbs, it contributes little to meaningful thematic separation.

• “human” may initially appear semantically rich, but its frequent appearance likely stems from repeated phrases such as “human emotion” or “as a human,” which often serve rhetorical or empathic functions rather than defining distinct topics. For that reason, it is also a candidate for removal.

4.2. Thematic structures and analysis

4.2.1. Female blogger in video 1

Using MDCOR, the comments were automatically clustered into latent themes. Based on the data from female blogger Video 1, this study extracted five core themes:

① "E-commerce experience complaints" High-frequency occurrence of fraud and logistics abnormalities, reflecting the anxiety of shopping risks, such as "receiving empty parcels" and "platform stealing credit card.

② "Emotional praise" is "too beautiful" and "I need this", highlighting the pleasure of the visual impact of AI art;

③ "China Related Interaction" uses made in China with joy expressions to convey cultural identity and positive emotions;

④ In "Intimate Interaction and Naming", the audience nicknames AI products such as "call it Emmy" to project deep emotions;

⑤ "Warm Appreciation" continues the naming interaction and treats AI works as warm creations.

These themes have been verified by co-existing word statistics - high-frequency words closely revolve around "experience, emotion and interaction", presenting high consistency. As shown in Figure 1, the distribution of emotions shows that: positive emotions such as joy and trust are absolutely dominant, perfectly echoing the video elements of dream unboxing and bright pastel visual.

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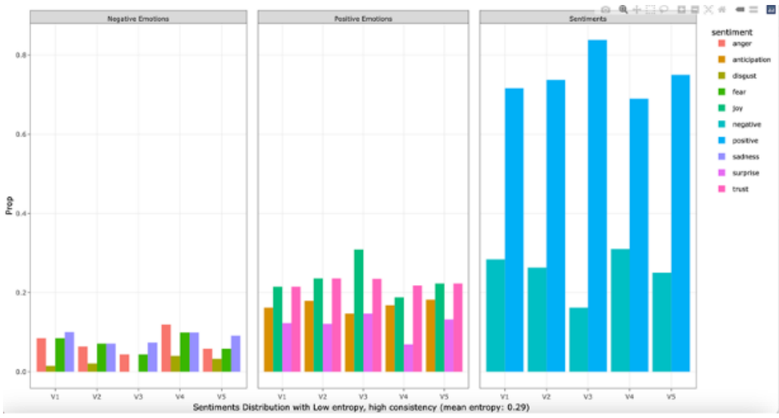

Figure 1. Emotional distribution of female blogger in video 1

For example, "joy" corresponds to 128 comments, and "positive" corresponds to 206 comments, see Figure 2. Negative emotions only appear sporadically in "e-commerce complaints". The low entropy value (0.29) shows that emotions are highly focused - the audience embraces the "beauty" of AI art without reservation, and only doubts in the transaction link. More importantly, our preset emotional associations such as "dream unpacking → expectation" and "bright color → joy" completely match the data, see Figure 3. This proves that the visual design of AI art can indeed accurately trigger the audience's emotional resonance, and can be quantitatively verified by comment data.

Video Element	Emotion Tags	Evidence (Node Size)
Playful unboxing of dreamy AI items	😍 anticipation	N = 93
Bright colors, pastel visuals	😊 joy / ❤️ positive	joy: 128 / positive: 206
Fantastical vs. realistic tension	😮 surprise	N = 66
Faith in AI creativity and execution	🧡 trust	N = 126
A few product fails or disappointments	😟 sadness / 😠 anger	sadness: 49 / anger: 42

Figure 2. Emotion-comment correspondence table for female blogger in video 1

Figure 3. Aggregated word cloud for female blogger in video 1

4.2.2. Male blogger in video 2

Turning to the comments of the male YouTuber Vedio 2, the data shows a completely different "contradictory sense". Through thematic modeling, this study finds two core themes:

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①"Online Shopping Fraud Warning" repeatedly discusses "fraud methods" and "rights protection experience", such as platform refuses to refund,highlighting the vigilance against the risk of AI product transactions;

②"AI product controversy" focuses on "Chinese production" and "compensation plan" such as made in China but shipped overseas,refracting the complex attitude of transnational transactions.

These two themes present a weak correlation through cross-thematic distance analysis - fraud warning and product experience "fight separately", reflecting the low consistency of comments. As shown in the Figure 4, looking at the distribution of emotions, the medium entropy value (0.496) means that emotions are more dispersed: anger accounts for the highest proportion of negative emotions; but positive emotions still have a place, such as "AI-generated wooden houses exceed expectations". Form a mixed emotion of "like but suspect that it is a scam". As Figure 6, the word frequency comparison is more intuitive: "scam" appears 27 times, "joy" appears 160 times - the audience's contradictions of both expectation and vigilance of AI art are "naked" by the data.

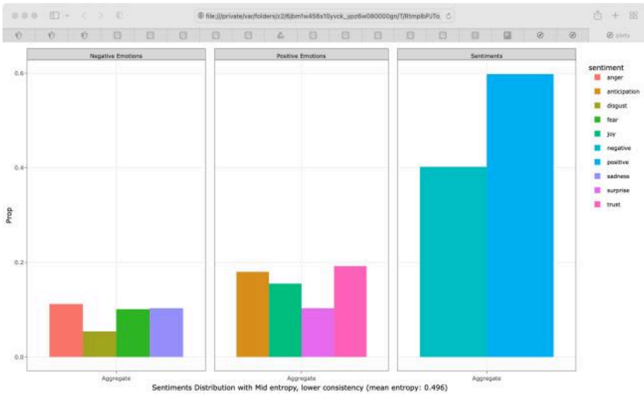

Figure 4. Emotional distribution of male blogger in video 2

Video Element	Emotion Tags	Evidence（Node Size）
AI - related product experience	curiosity/Skepticism	popper：38/scram：27
Debate on AI creativity	Excitement	joy：160 smile：22
Discussion on AI execution	Frustration/Optimism	cry：25
Male - led AI opinion sharing	doubt/attention	scarm：27

Figure 5. Emotion-comment correspondence table for male blogger in video 2

Finally, look at the aggregate group word cloud: the core words "joy", "tear", "heart" and "scam" coexist, echoing the title "Group: Aggregate, Low entropy, high consistency, see Figure 7. Although the emotions of a single video are diverse, the overall data set is still highly aggregated around the "emotion and controversy of AI art" - which is the commonality of cross-video and the underlying logic of AI art communication.

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Figure 6. Aggregated word cloud for female blogger in video 1

4.3. Comparative analysis

The QAP analysis (Figure 7-9) reveals that Topic V1 and V3 exhibit a very low correlation (Rho = 0.129), suggesting substantial differences in emotional framing and discourse. Topic V1 is grounded in consumer caution and rational warnings, whereas. Topic V3 embodies a playful, meme-like mode of expression, and is accompanied by high-frequency emoji. Topic V2 and V3 have a strong but not statistically significant association (Rho = 0.416). Both have emotional and performing characteristics, but have different style orientations.

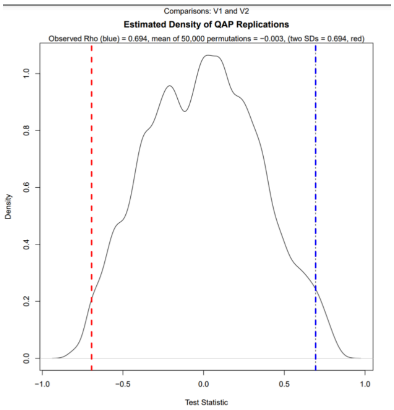

Figure 7. Estimated density of QAP replications- comparisons: V1 and V2

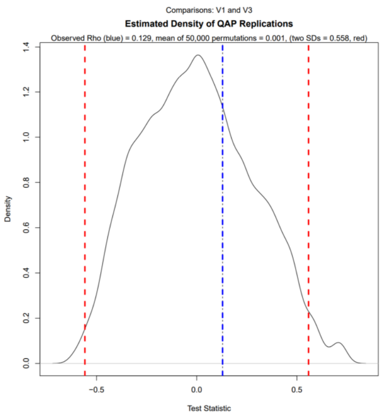

Figure 8. Estimated density of QAP replications- comparisons: Vi and V3

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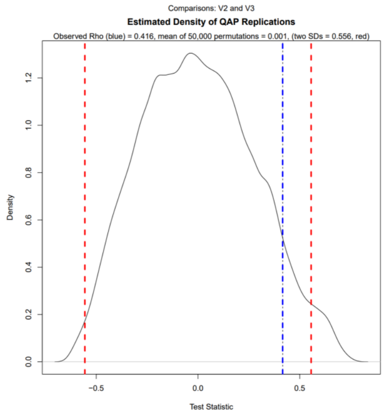

Figure 9. Estimated density of QAP replications- comparisons: V2 and V3

The QAP analysis (Figure 10) shows that V3 performs well, especially on trust and satisfaction. In contrast, the tone of V1 is more mixed or even negative, which is consistent with its discussion of transaction risks. V2 is quite interesting: although it is not as positive as V3, it is not as negative as V1.

From an analytical point of view, it begins to become particularly intriguing. Although V2 is related to dopamine beauty, the data shows a large number of negative emotional labels. Moreover, this conclusion is contrary to our previous qualitative research, which believes that the female YouTuber's participation is attractive, desirable, and enthusiastic as a whole.

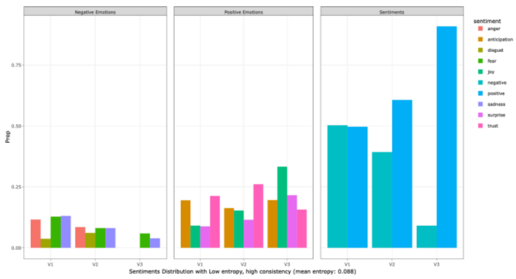

Figure 10. "Emotional distribution and polarization characteristics of V1, V2, and V3"

There may be three reasons for the above differences: 1. Conflicting emotions. For example, a "praise with a caveat" mode, such as "I love this, but I think it's too expensive." This kind of sentence pattern will mix emotional information that is not in harmony with each other. Subsequently, the emotion analysis system tends to grab both ends at the same time and classify the statement into different emotional categories.2. how people of different genders react to art. Therefore, female creators who create "aesthetic" content often receive praise or gentle criticism, while male designers who present the same image may receive more negative or joking comments, especially in beauty or lifestyle topics. In other words, people's existing beliefs about gender and appearance will affect their emotional expression and labeling. 3. The issues with automated sentiment analysis. Most tools are difficult to deal with usage different from their existing experience, because they have difficulties in parsing complex sentences, especially when the sentence contains contrast conjunctions such as "but". In actual analysis, regardless of the context, the weight of negative words usually increases.

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5. Results

We use emotion analysis to investigate the public's reaction to AI-generation art on YouTube, so as to identify the important emotions and themes in the current AI art discussion. The results show that emotions are not universally homogeneous; on the contrary, they are polarized and dependent on context. The audiences who support this concept often expresses pleasure, admiration and joking with memes, emojis and comments. We call this phenomenon dopamine aesthetics. These recurring emotional clusters indicate how AI art is embedded in the performance and emotion-driven culture of social media - "wonders" can most drive participation.

However, when the discussion turned to authenticity, economic value and suspicious fraud, many audiences showed suspicion, concern and ethical uneasiness. This kind of interaction is scattered and messy, showing that ethical and economic considerations will break the consensus in a way that is different from aesthetic enjoyment.

The data also shows that there are still differences at the theoretical level. Benjamin's apprehension regarding the degradation of aura aligns with themes of skepticism and authenticity, whereas Kalpoka's "data-born aura" arises from AI's algorithmic inventiveness.

Barker's theory that reproduction always involves creative values alters our view of modern concern from a new problem to a cyclical echo. However, Skellington's views on algorithm generation have raised concerns about the replacement of human beings. The above views show that AI art involves not only the appearance, but also the redefinition of creativity, freedom and cultural authenticity.

This empirical evidence-based research shows that the public's discussion of AI art is delicate and contextual, reflecting the deep contradiction between "originality and authenticity", substitution and liberation. The society's view of AI generation art is not simply for or against it. Understanding these associations helps artists, developers and legislators, and promotes academic dialogue on how new technologies affect art, emotion and society.

Data demonstrates a "contradictory sense" from male YouTuber Video 2. The research identifies two main themes through thematic modeling:

•"Online Shopping Fraud Warning" commonly comprises "fraud methods" and "rights protection experience" (platform refusal of returns, etc.) to discourage AI goods purchases.

•"AI product controversy" revolves around "Chinese production" and "compensation plan", referring to the situation of production in China and delivery to other countries, highlighting the complexity of cross-border operation.

6. Conclusions

The analysis of YouTube reviews in this study shows that there is a significant differentiation in the public's response to the art of AI-generation. On the positive side, most comments are pleasant, happy and have a sense of humor, often accompanied by emojis, memes and short and emotional messages. The study defines this phenomenon as "dopamine aesthetics", that is, to promote immediate participation with strong visual impact.

On the negative side, the study found a large number of expressions of doubt, fear and ethical problems. People frequently discuss topics such as morality, originality, fraud and price.

Entropy analysis has significantly deepened our understanding of these dynamics: on the one hand, the clustering of "interesting/cute" comments is relatively stable, comes from the community, and changes little; on the other hand, the discussion around ethical and economic issues is more divergent and the entropy value is higher. In other words, people are more willing to interact with

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each other when they appreciate "beauty", and when it comes to money or ethical worries, their willingness to interact is reduced.

These findings are consistent with a variety of existing theoretical frameworks. Walter Benjamin's worries about the regression of "aura" are reflected in the continuous doubts about the artistic legitimacy of AI-generation; the concept of "data-born aura" proposed by Kalpokas helps to explain the public's infatuation with algorithm innovation and collective cultural production. Barker's historical research reveals that every major change in art technology triggers anxiety about replication; this means that the current discussion about AI art is not new, but part of the historical cycle. Finally, Skellington's discussion on algorithmic generation expands the scope of attention: AI art not only forces us to rethink "what is true", but also forces us to ask the meaning of "what is human" when human beings "create".

The above theories together constitute a solid framework for explaining the emotional and subject polarization models in this research data.

The tension between "controversy" and "cultural relevance" is not unique to AI art. Many people think that Marcel Duchamp's Fountain (1917) is not "real art" because he just took a toilet from the store and displayed it as art - a typical example. Because of its "unreal" or "non-original", the work has gained its halo and legitimacy, which also makes it a key component of Dadaism.

AI art is going through a similar process: like Duchamp's work, it challenges the authenticity, legality and value judgment of traditional art. This shows that competitive discussion at the public level will not weaken the value of AI art, but may become a key factor in improving the status of AI-generation art culture. Of course, some limitations of this study should also be noted.

First, the study only samples a small number of YouTube videos with similar length and heat. Although it is easy to compare, it limits the diversity of views.

Second, automated emotion analysis is good at identifying overall trends, but it is easy to distort the difference between details and semantics. For example, the model is difficult to properly interpret such as "I love this, but it feels overpriced." Such a mixed statement may lead to some misclassification.

Third, the research conclusions are platform-limited. YouTube comments are deeply influenced by community-driven interaction; the situation may be different on other platforms. Take TikTok as an example, it relies more on trends and viral transmission, as well as short video forms and effects, to provide users with broader content and aggregate data for their algorithms.

These restrictions mean that although the conclusions are reliable within the established range, they do not necessarily represent a long-term sustainable model.

This study shows that AI art is neither simply accepted nor simply rejected; on the contrary, it is constantly defined in public debate and bargaining. Innovation and commercialization, authenticity and duplication, liberation and substitution are key ideas in this fight. This study substantiates theoretical assertions that public opinions are intricate, contextually influenced, and indicative of macro-cultural apprehensions.

AI art creates the "aura" something that can be shared, spoken about, and has cultural significance. Talking about AI art, like Duchamp's Fountain, shows that it will change how people appreciate art.

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