Exploring the Evolvement of User Engagement in Online Creative Community under the Surge of Generative AI: A Case Study of DeviantArt

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The rise of AI-generated content (AIGC) is transforming online creative communities (OCCs) and posing challenges to their regulation. The interacting behaviors, such as sharing artworks with descriptions, commenting on creations, and creators' subsequent replying are the essential components of user engagement in these communities. Understanding the influence of AIGC on the evolving user engagement could be helpful for community regulation. In this work, we collect 235K posts and their associated 255K comments from DeviantArt, a large creative community allowing uploading AIGC. Through open coding, we identify five categories of practices in describing and commenting on artworks, respectively. A set of deep learning models are applied to classify the posts and comments. We then combine time series regression analysis, causal inference analysis, and logistic regression analysis, to examine the impact of the surge of AIGC on user engagement. Results suggest that AI-generated artworks show a decreasing emphasis on the content of creations but an increasing trend toward commercial and promotion purposes. AI-generated artworks emphasize less on IP issues than human-created ones, while the awareness of IP issues drops for human-created artworks with the growth of AIGC as well. Although comments with high sentiment valence, for peer bonding or for requesting usage positively predict the reply behavior for human-created artworks, community members are less likely to maintain these interactions as AIGC rises. Finally, we discuss insights and design implications for OCCs.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**.

Additional Key Words and Phrases: Online creative community, AI-generated content, generative AI

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1 Introduction

Recent innovations in generative AI technology have significantly improved the quality of AI-generated content (AIGC), attracting more creation shared across online communities. As AIGC is progressively replacing user-generated content (UGC) [121], it is also reshaping the norms within online communities. For example, online creative communities like DeviantArt [27] allow creators to upload their artworks (either UGC or AIGC) along with descriptive information, such as the information in the creation process. These communities provide opportunities for creators on skill learning, entertainment, and professional development by showcasing creation and interacting with remote peers [38, 59]. Generative AI tools, such as DALL-E, Stable Diffusion, and Midjourney, enhance these benefits as they increase the productivity of creators and encourage broader participation by lowering barriers to artwork creation [63, 129]. On the other hand, generative AI poses new challenges to the regulation of online creativity communities. These challenges include the potential for low-quality creations, conflicts in attitudes toward AI-generated content (AIGC), and complex copyright issues [3, 80].

The success of an online community relies on the user engagement, which could evolve when the community is impacted by external events [47]. While previous studies indicate the potential benefits and risks of generative AI techniques to the creative community, we still lack a quantitative understanding of the influence of AIGC on the creative community through the lens of user engagement. In this paper, we define user engagement as community member's participation and dynamic interaction with creative output and remote others on the platform. We propose to inspect it from the following perspectives: 1) how creators manifest a creation under new trends (indicating creative practices in the community), 2) how creators describe their works to the community (revealing motivations to share in the community [17, 18, 48], 3) how consumers comment on a creation that reflects their attitudes towards the creation, and 4) whether creators respond to these comments that contribute to deeper social interaction in the online space [23]. Understanding the evolving user engagement in response to the technology-driven surges from these perspectives could provide valuable insights for effectively regulating online creative communities to foster creativity and accommodate members' needs in the era of AIGC [15, 39]. Therefore, we raise the following research questions:

- RQ1. To what extent has generative AI artworks been adopted in the community?
- RQ2. How do creators describe the shared artworks in the community and how does such practice evolve?
- RQ3. How do consumers comment towards creation and how does such practice evolve in the surge of AIGC?
- RQ4. How do creators' engagement with community members evolve in the era of AIGC?

To this end, we utilized data from DeviantArt, one of the largest online communities dedicated to sharing artworks including AIGC, to address the research questions. Our data involved randomly sampled 235K posts uploaded from August 2020 to November 2023, covering the period before the release of generative AI techniques to the prevalence of AIGC. These posts are associated with 255K consumers' comments and 119K creators' replies. We trained a visual-based AI art classifier to identify the AI-generated artworks in the sampled data. In RQ1, We confirmed the AIGC surge in the platform and identified the prevalence period of AIGC began in September 2022 through a time series algorithm (Section 4.1).

We then randomly sampled 800 posts and 1000 consumers' comments to reveal how creators described their shared artworks (for RQ2) and how consumers commented under artworks (for RQ3) through open coding. We figured out five categories of creators' description practices – context of creation (e.g., creation scenario), process of creation (e.g., adopted techniques), content of creation, dissemination of creation (e.g., intellectual property (IP) disclaimer, commercial), and community interaction around the creation. We also identified five categories of consumers' commenting practices – content of creation (e.g., judgment, interpretation), knowledge exchange (e.g., providing suggestions, investigation), social interaction (e.g., peer bonding, fandom building), dissemination of creation, and sensitive content. We fine-tuned deep learning models to classify the creators' descriptions and consumers' comments in the entire dataset. For RQ2 and RQ3, we combined the interrupted time series (ITS) regression with Bayesian structural time series (BSTS) analysis to reveal how the prevalence of AI influences the creators' describing and consumers' commenting behaviors. For RQ4, we conduct logistic regression to understand how factors related to creators' reply behavior vary as AIGC surges.

Results suggest that AI-generated artworks show a decreasing emphasis on the content of creations but an increasing trend toward commercial and promotion purposes. AI-generated artworks emphasize less on IP issues than human-created ones, while the awareness of IP issues drops for human-created artworks with the growth of AIGC as well (Section 4.2). Although comments with high sentiment valence, for peer bonding, or for requesting usage positively predict the reply behavior from human-created artworks (Section 4.4), consumers decrease these interactions with human-created artworks as AIGC rises (Section 4.3.1). We discuss the design implications, such as channel design, optimizing commenting strategies, and community collaborative curation in Section 5. Our studies reveal the impact of generative AI on the user engagement of the creative community and provide insights for community moderation under the surge of AIGC.

2 Related Work

In this study, we highlight relevant literature on the interaction between AI and content creators, as well as social media users, to better situate the study.

2.1 Generative AI and Content Creator

As people increasingly incorporate generative AI into their content creation process to enhance quality and productivity [13], HCI researchers have proposed various human-AI co-creation tools for different domains. These tools include applications for design space exploration [24, 114], creative writing [21], image generation [79, 115], music creation [7, 81] and video creation [19, 113].

The prevalence of human-AI co-creation tools has prompted researchers to investigate the co-creation itself. They are examining the motivations and barriers that creators encounter when adopting generative AI [3, 102, 104], as well as the usage patterns of generative AI [8, 32, 70, 82, 91, 123]. Additionally, a significant focus is placed on understanding the impact of generative AI on creators and their co-creative practices.

Studies have identified this impact from different perspectives. For productivity, Noy and Zhang [89], Zhou and Lee [129] found that generative AI improved both efficiency and quality in professional writing and text-to-image generation. Doshi and Hauser [33] in their experimental study also found generative AI increased the writers' creativity by making their works better written and more enjoyable, albeit at the expense of diversity. Despite the creativity associated with AI-generated works, the black-box nature of generative AI can lead to a sense of indirectness and lack of control during the creation process [107]. Moreover, generative AI may cause economic loss to creators, abuse of their copyright, and thus reluctance in personalized crafting and content sharing [63, 96]. For AI art creators, they may face an identity crisis as serious artists, find their creative processes restricted by the attributes of AI tools [9], and often feel underappreciated by audiences [5, 9, 85]. Additionally, generative AI may negatively influence creators' careers, such as causing a decrease in the number of job posts related to image creation [25].

In short, previous studies have provided insights into the impact of generative AI on creators' careers, their creative outputs, and the direct creation process. However, content creation, viewed as a creative design process, inherently requires iterations to achieve better presentation outcomes [35, 125]. This iterative process is facilitated through interactive activities such as sharing the creation, interpreting audience feedback, and making subsequent revisions [41, 73], which received limited attention in existing research. Different from previous works, our study focuses on the practices of creators in sharing their work and engaging in online interactions, as well as how consumers engage with artworks. By analyzing data from an online creative community, we aim to gain a deeper understanding of these dynamic practices.

2.2 Impact of Generative AI to Social Media Platforms

Recent studies indicate a growing prevalence of AIGC across various social media platforms. For instance, AIGC has significantly impacted news media platforms, influencing the topics, sentiments, and biases of news content [36, 52, 88, 127]. On Twitter, generative AI has produced numerous images, with a shift in themes towards more artistically sophisticated content, such as human portraits [16].

As mentioned earlier, the influx of AIGC has transformed the overall characteristics of these platforms. Despite being perceived as neutral, generative AI can be prompted to disseminate harmful content in social media platforms, including hate speech [42, 45, 76] and NSFW (not safe for work) materials [37, 108, 120]. These undesirable outputs of generative AI, coupled with other risks such as the spread of misinformation [74, 109, 110], have raised significant ethical concerns and led to the discussion on regulations by both researchers [31, 43, 50, 51] and consumers [65, 98].

The consumers, i.e., the users of social media, may be directly influenced by prevailing AIGC contents and consequently alter their behaviors. Traditionally, social media platforms are designed for human interaction. However, the emergence of AI as a social agent, capable of exhibiting human-like speech and behavior [95], introduces novel interaction patterns to human users within online communities. Human-like interactions with LLM conversation agents can enhance the interaction between both posters and commenters [111]. Yanardag et al. [126] deployed an AI-based collaborative horror writing bot on Twitter, which significantly impacted readers' emotions, particularly for co-created stories. However, recent studies suggest that such interactions may also lead to overreliance on or unsafe use of AI agents. For example, users may be more likely to disclose private information to human-like chatbots [6, 119].

On the other hand, the influence of static AIGC on user engagement across social media platforms presents mixed evidence. In online knowledge communities, answers generated by LLMs have influenced user perceptions and activities, leading to a decline in viewing and posting but an increase in the liking of answers [12, 54, 64]. Huang et al. [57] revealed that the integration of generative AI within Lofter led to a significant decrease in content creators' activity, except for more popular content creators who were less likely to decrease their activity. Zhang et al. [128] studied the impact of AI-generated voice on TikTok videos and suggested that the use of AI voice is not significantly correlated with likes and comments per view per creator and week. Wei and Tyson [117] explored the impact of AIGC on the Pixiv community, noting an increase in content creation but a decrease in viewing and commenting.

However, there still remains a gap in understanding how community interactions are influenced by user-initiated AIGC. Deeper community interactions, including sharing, commenting, and replying, as opposed to chatting and viewing, may better reflect the inherent characteristics of all participants and the entire ecosystem. The rapid development of generative AI technologies, like other triggers to the communities [14, 46, 47, 53, 78], is continuously reshaping the paradigm of content production, adding a new dimension to investigating these characteristics. In this work, we utilize DeviantArt, a leading online creative community as a case to characterize the user behavior (i.e., posting, commenting, and replying) evolvement in the influx of AIGC.

3 Method

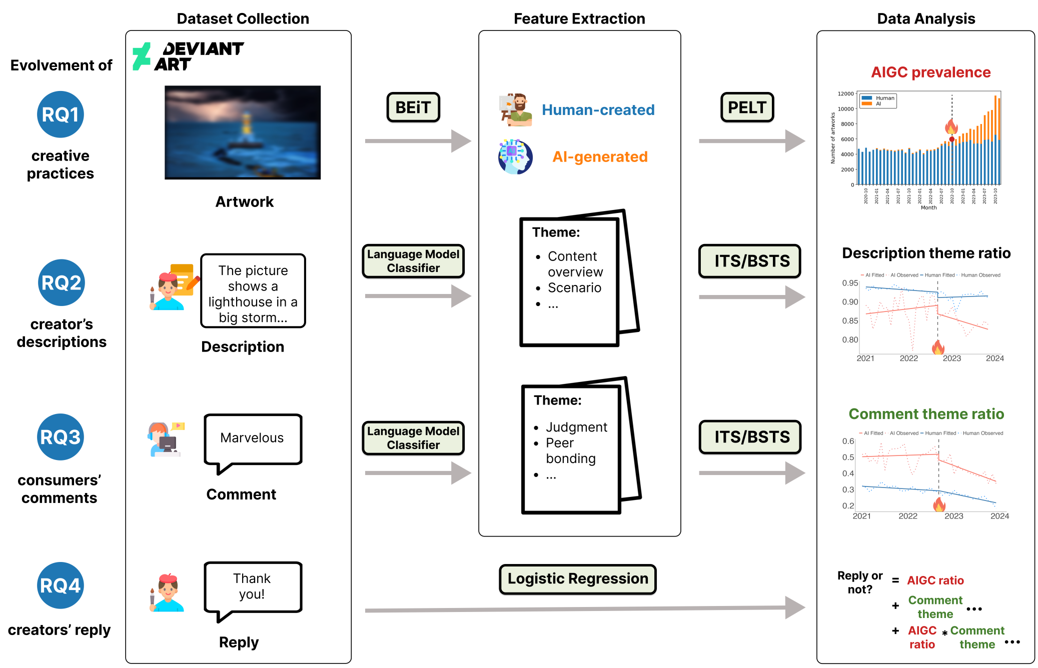


Fig. 1. Research workflow for examining user engagement variations in response to the prevalence of generative AI. **Dataset Collection**: We scraped artwork-level information from the DeviantArt platform, including the artwork, the associated descriptions, comments, and replies. **RQ1**: Fine-tuned computer vision models were applied to classify artworks into AIGC and UGC. The monthly percentage of AIGC artworks was calculated, and the PELT algorithm identified September 2022 as a salient change point marking the surge of AIGC. **RQ2 & RQ3**: We open-coded the respective engagement patterns of creators' descriptions and consumers' comments to understand how community members engage with creation in the community. The impact of the AIGC surge on these patterns was modeled using two quasi-experimental approaches: ITS and BSTS. We compared the engagement patterns in the recent AIGC era with Chi-squared test and T-test. **RQ4**: Multiple logistic regression analyses explored how factors related to creators' reply behaviors evolved during the AIGC surge.

We first introduce the basic setting of the research site and how we scrape the data (Section 3.1). We then illustrate the approach to distinguishing AIGC and UGC with deep learning models (Section 3.2), providing the opportunity to reveal the trend of creation practice (RQ1). In particular, we adopt the PELT algorithm to identify when salient changes in creation practice happened in the community. Next, we characterize creators' descriptions of AIGC versus UGC artworks (Section 3.3) and consumers' comments (Section 3.4) toward these artworks via open coding. We apply the quasi-experimental methods (i.e., ITS and BSTS analysis) to the result to examine the impact of the

AIGC surge on community members' engagement, and compare the engagement patterns under AIGC and UGC with statistic tests (RQ2 for creators and RQ3 for consumers). Finally, we conduct regression analysis to explore how factors related to creators' reply-to-comment behavior vary as AIGC arises in the community (Section 3.5), providing a more comprehensive view of generative AI's effect on creator engagement beyond sharing. Figure 1 illustrates the general research workflow of the study.

3.1 Research Site and Data Collection

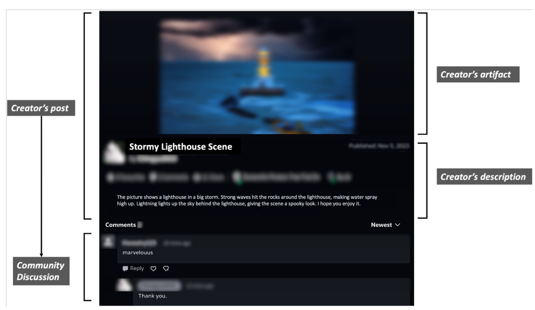


Fig. 2. Example artwork published on the DeviantArt platform. We decrease the resolution and obscure sensitive information for copyright and privacy concerns. We slightly paraphrased the content in the post so that the post could not be searched.

DeviantArt is one of the largest artist communities, which is reported with over 700 million page views per month in 2024 [29]. Figure 2 is an example of artwork published on the platform. Artists can share their created artifacts along with an introduction (such as the artifact title and a description). They can also serve as consumers who comment on other creators' artifacts. The DeviantArt platform does not prohibit the adoption of generative AI in the creation process, and therefore, could act as a lens to investigate the impact of AIGC in the community.

On DeviantArt, each artwork is assigned with a unique ID by the platform. In our study, we examined a random sample of 1000 artworks published in November 2023 and found a Spearman correlation of over 0.97 between the ID and the artwork publication time. This high correlation indicates that most artwork IDs are assigned in ascending order by their publication time, with more recent projects receiving larger IDs. That is, sampling and ordering by artwork ID is almost equivalent to sampling and ordering by publication time. To capture the recent trend of community content, we scraped artworks by randomly sampling IDs starting from an ID in July 2020. We obtained around 250K valid project responses from DeviantArt.

We took the following steps to filter the data. First, we restricted the data to projects published between August 2020 and November 2023 to reflect the recent trends in the community. After this step, around 240K projects remained. Next, we removed projects that did not fall under the category of "visual art" (a pre-defined category on the platform) to ensure focus solely on those projects related to artwork sharing. We also eliminated projects that contained GIFs instead of static images, as dynamic images could pose difficulties for analysis in subsequent procedures. Finally, we obtained a dataset of 235,528 artifacts from 122,707 unique users, spanning the period from August 2020 to November 2023 (for RQ1 and RQ2). The scraped information includes the URL of the artifact and the metadata associated with the posts, such as the title, description, creator username, and the received comments.

We adopted several procedures to pre-process the scraped comments. First, we removed the comments that have been hidden by community moderators, creators, or commenters themselves. Next, we removed comments presented in picture format to concentrate on text-based analysis.

Eventually, we have 63, 824 projects that receive at least one consumer comment, leading to 255,430 comments from consumers for analyzing the commenting behavior (RQ3). We figured out 119,443 replies from original creators towards these comments, leading to 119,443 comment-reply pairs for analyzing the creators' reply behavior (RQ4).

3.2 Generative AI Techniques Identification

We first utilized the meta-data associated with the artwork to distinguish whether it was created using AI. Following the practice in [16, 129], we labeled the artworks published before 2021 as human-created projects, as the earliest text-to-image model, DALL-E was released in January 2021. This step identified a total of 22,747 human-created projects.

Additionally, the DeviantArt platform requires users to indicate whether they utilized AI techniques in their creations [28]. For the remaining data (projects published after 2021), we examined whether the creators disclosed the use of AI in the attribute associated with the project, and identified 20,259 projects with AI-creation disclaimers. We then trained the AI-artwork detector using the visual information from the labeled projects. The training, validation, and test sets were randomly split, with 18,747/2,000/2,000 human-created artworks and 16,259/2,000/2,000 AI-created artworks, respectively. We fine-tuned multiple vision models on the training set, including CNN-based ResNet-50 [55], and Vision-Transformer-based models such as ViT [34], BEiT [4], and DINOv2 [92]. We compared their performance on the validation set. The BEiT model, which was pre-trained on ImageNet-22k dataset [26], achieved the best performance (precision = 0.98, F1 = 0.95, AUC = 0.988) on the validation set following the fine-tuning process. Subsequently, we evaluated its performance on the test set, where it achieved 0.98/0.96/0.989 on precision, F1, and AUC, respectively. We present the confusion matrix of the test set in Table 1. It suggests a robust recognition ability across the binary categories. We evaluate the model performance in recognizing AI-generated artworks across time by dividing testing data into 10 bins according to the chronological order of the publication time and measuring the F1-score on each fold. The result (F1-score - mean: 0.97, std: 0.01, min: 0.95, max: 0.98) demonstrates the model's consistent effectiveness in recognizing AI-generated artworks across time. With the BEiT model, we predicted whether the artwork integrate AI in the remaining 192,522 projects. Our final dataset contains 197,126 human-created artworks (from 112,656 unique creators) and 38,402 AI-generated artworks (from 13,415 unique creators). The mean/SD/median/75th percentile/99th percentile of user-uploaded projects in the sampled data is 1.75/4/1/2/11 for human-created artworks, and 2.86/7.46/1/2/28 for AI-generated artworks. Interestingly, we identified 18,143 AI-generated artworks without explicitly disclosing the AI usage in artwork attributes. One potential reason is that creators may be afraid of receiving negative comments if they disclose the use of AI [3]. Another explanation is that creators might prefer their artworks to be evaluated based on artistic merit rather than on how they were created [56]. Future works could delve deeper into the reasons behind this phenomenon through qualitative research.

Table 1. Confusion matrix of AI-artwork detector performed on the test set.

	predicted human-created artworks	**predicted AI-generated artworks**
actual human-created artworks	1961	39
actual AI-generated artworks	117	1883

3.3 Creator Sharing Practice Identification and Classification

3.3.1 Creator Sharing Practice Identification. We utilized an open coding approach [68] to identify creators' practices in describing artworks in the community. Initially, 150 sample posts were independently coded by three researchers, focusing on the practices related to sharing creations. Specifically, they analyzed two distinct components of the posts: the artwork title and the artwork description. The artwork title provides a brief overview of the creation, while the description allows for a more detailed disclosure. Then they got together to compare the codes they had identified and engage in discussions to resolve the disagreement. They refined the definitions of certain codes based on the discussions, and re-coded the 150 posts. For instance, they observed that most titles merely provided a general overview of the created artifact, often overlapping with the description. Consequently, they merged the codes for the title and description. They repeated these steps until they achieved a substantial level of agreement among the three coders (Gwet's AC1 $\geq$ 90%). We use Gwet's AC1 to measure the inter-rater reliability, as it is more suitable and stable than other measurements (e.g., Cohen's κ) for scenarios where certain codes (e.g., IP disclaimer) are rare in the sampled data [49]. After the iteration process to refine the codebook, they finally discussed inter-code connections and clustered related codes, yielding high-level categories.

Through our open coding, we uncovered multiple codes in creators' sharing and grouped them into the following perspectives related to creation. Table 2 lists detailed examples for each code.

Context of creation pertains to the circumstances and influences that surround and contribute to the creation of a work. This includes the specific scenario in which the work was created (such as the time and location), any original references used (such as a fanart piece based on an existing work), and the source of inspiration for the work.

Process of creation refers to the methods and procedures used in the creation of the work. This includes the tools and techniques utilized, any collaborative efforts involved in the production, the use of artificial intelligence in the creation process, and any prompts or guidelines that were followed.

Content of creation focuses on the actual content of the work. This could be a general overview of the work or a detailed narrative of the content in the artwork.

Dissemination of creation involves how the work should be shared, distributed, or commercialized. This could include any intellectual property (IP) disclaimers associated with the work, instructions on how the creation can be used or reproduced, and any commercial efforts, such as selling the artwork.

Community interaction around creation pertains to the social aspects of the creative process and the community's response to the work. This includes the creator's self-introduction and self-promotion, the socialization that occurs around the work (such as discussions or debates), and any invitations for comments or feedback on the work.

3.3.2 Creator Sharing Practice Classification. Once the codebook was finalized, two of the three coders coded another 50 posts independently, and they reached a high level of agreement (Gwet's AC1 $\geq$ 88%) on each dimension. After establishing the substantial agreement between the two coders, they randomly sampled another 600 posts, each coding half of the posts separately. Eventually, we got 800 coded posts for training a classification model.

We randomly split 60%, 20%, and 20% data into the training, validation, and test sets respectively. We adopted multiple language models for predicting the description category, including BERT-base-uncased [30], Bertweet-base [87], Bertweet-large [87], Bert-base-multilingual-uncased [30], Multilingual-e5-large-intstruct [112], and the state-of-the-art open-sourced large language model Llama 3 [1]. We fine-tuned these models to predict each category separately and chose the best model for each dimension. Detailed model performance is listed in Table 3.

Table 2. Creators' sharing practice coding scheme and examples. We slightly paraphrased the content in the post so that the post could not be searched. We use [USERNAME] to represent the original username to protect users' privacy. We reported the distribution of each code in the entire annotated data.

Category	**Code**	**Definition**	**Example**
Context of creation	Scenario (10.5%)	Provide the circumstances, location, time of the creation	*– I had an assignment yesterday where I had to draw 3-5 objects that I had in my household...*
	Inspiration attribution (11.5%)	Acknowledges or credits a specific source of inspiration, such as artwork reference and ideas	*– A fan art of "The Batman";* *– Credit to [USERNAME] for the wonderful ideas*
Process of creation	Tools and techniques (5.875%)	The tools and techniques adopted in the creation	*– Background added from photoshop*
	Collaborative information (2.125%)	Acknowledge or credit other members in the creation process	*– a friend and i wrote it*
Content of creation	Content overview (88.75%)	Brief introduction of the objectives in the artwork	*– Roses at the wall*
	Content narrative (20.25%)	Provide explanation of the objectives in the artwork, such as character relationship, attributes, and stories	*– This is my original character. A therapist who specializes in empowering women utilizing methods that many might feel are unorthodox. Her philosophy: if a pathetic male is ruining a woman's life by refusing to accept a female's power over them, then the best thing to do*
Dissemination of creation	IP disclaimer (8.125%)	Mention the copyright information of the creation	*– Character(s) presented do not belong to me*
	Usage instruction (5.25%)	Guidelines on using the artworks	*– Free of use with credits*
	Commercial (6.5%)	Information on purchasing the artwork	*– Status: OPEN (2/5 slots)Terms of service: Payment is upfront*
Community interaction around creation	Socialization (12.75%)	Provide personal information or experience to connect with the community	*– You can call me [USERNAME]!! Another reason I made a dA is to register my personal grow*
	Interaction guidance (4.125%)	Suggestions for interacting for the artwork	*– What's your fave object out of all of these?*
	Promotion (11.375%)	Provide external links to other artworks or portfolio	*– Follow my work here too: twitter.com/[USERNAME]*

In order to automatically predict the description of each post, a total of 12 categories in five topics were classified using binary classification models. Six deep learning models that are commonly used for text classification tasks were tested in order to automatically predict these description categories. Despite the existence of 800 labeled descriptions for each category, the dataset is extremely unbalanced in certain categories due to the presence of rare categories (e.g. Collaborative with only 2%). This makes it difficult to train the model. To address this issue, we employed a widely utilized data imbalance solution, namely balanced softmax loss [99], with the objective of enhancing the model's performance on a few categories within the context of the long-tail problem. This approach involves incorporating the number of distinct labels into the calculation of the loss function, thereby balancing the impact of each label on the loss, which enables the model to consider the minority label during training, rather than predicting them all as a single label. The model was trained on the training dataset and evaluated on the validation dataset, after which the final performance was assessed on the test dataset.

Table 3. The model performance on F1-score with the test dataset of each description category (the bold for the best performance). We also report the ratio of each code in the entire predicted dataset.

	Context		Process		Content		Dissemination			Community Interaction		
Model_name	Scenario	Inspiration	Tool	Collaborative	Overview	Narrative	IP	Usage	Commercial	Socialization	Guidance	Promotion
BERT-base	0.765	0.711	0.727	**0.750**	**0.981**	**0.842**	0.769	**0.842**	0.762	0.700	**0.800**	0.789
Bertweet-base	0.812	**0.762**	**0.762**	0.667	0.976	0.828	0.769	0.737	**0.870**	**0.778**	0.769	0.800
Bertweet-large	**0.848**	0.706	0.727	0.571	0.981	0.746	**0.857**	0.500	0.870	0.757	0.800	**0.895**
Bert-base-multilingual	0.651	0.653	0.467	0.571	0.844	0.590	0.233	0.304	0.409	0.417	0.333	0.508
Multilingual-e5-large	0.492	0.698	0.486	0.286	0.981	0.831	0.339	0.240	0.750	0.508	0.435	0.865
Llama 3	0.511	0.540	0.526	0.122	0.955	0.585	0.615	0.696	0.714	0.625	0.400	0.750
ratio	5.28%	13.7%	6.7%	1.25%	87.08%	18.98%	3.16%	3.96%	3.43%	13.13%	4.45%	15.29%

3.4 Consumer Commenting Practice Identification and Classification

3.4.1 Commenting Practice Identification. We conduct thematic analysis on the project-associated comments to identify consumers' practices in engaging with the creation. Initially, 200 consumers' comments were randomly sampled. Three researchers first followed an established taxonomy for design feedback. They independently coded these samples and then got together to compare the codes. They further merged some codes in the original taxonomy that showed similar meanings and removed several codes that rarely appeared in the sampled data. In addition, they also added four new codes in the data, including *requesting usage*, *peer bonding*, *fandom building*, and *sensitive content*. After rounds of discussion, they finalize the codebook and achieve a substantial agreement (Gwet's AC1 $\geq$ 73% for each code. These codes can be grouped into five categories as illustrated in Table 4), including

Content of creation refers to how consumers evaluate and make sense of the content. It could be *judgment*, where consumers saw and rendered some assessment of its quality. They are often in an evaluative tone. It also contains the code of *interpretation* where consumers engage with the creation by interpreting its meaning and making associative connections to other related objects or personal experiences.

Knowledge exchange refers to exchanging knowledge, information, or critiques between consumers and creators. Consumers can provide concrete recommendations for current creations or brainstorm revision potentials or future creations. Consumers can also investigate information about creation, such as processes and contexts in creation.

Table 4. Consumers' commenting practice coding scheme and examples. We slightly paraphrased the content in the post so that the comments could not be searched. We reported the distribution of each code in the entire annotated data.

Category	Code	Definition	Example
Content of creation	Judgment (31.4%)	Comments that are in an evaluative tone, often convey an assessment of the design	*– It's such a beautiful style;* *– shame it's AI stuff like this is so much better when talent is used*
	Interpretation (35.5%)	Comments where someone reacts to what they saw and tries to make sense of the creation. The consumer may also imagine the plots in the image, make connections to other objects, or recall personal experiences	*– A smol pika!;* *– Undyne: I Don't Really Like Hugs;* *– It looks like living in a close up of a Mandelbrot series;* *– When I was dating my wife before we were married ... [personal experience related to the plot in the creation] ...*
Knowledge exchange	Providing suggestions (2.6%)	Giving specific advice about a particular aspect of the creation (direct recommendation) or making statements/rhetorical questions about imagined possibilities for the creation (brainstorming)	*– Here's some collector models too for reference: [link to the website]*
	Investigation (6.1%)	Soliciting information about creation, such as the process and context in creation	*– Which AI did you use? I am trying to find a good one*
Social interaction	Peer bonding (20.5%)	Creating positive emotional or interpersonal connections with the creator, e.g., support the creator	*– wonderful, keep up the good work!*
	Fandom building (3.3%)	Disclosing fan identities by discussing character or story settings in the original IP	*– To me anyone associated with Deathwatch or is a Child of the Watch (including the covert Din Djarin was a part of before he was "banished") are not only traitors but not Mandalorians at all, just terrorists wearing armor they have no right to wear.*
Dissemination of creation	Requesting usage (4.7%)	Requesting purchasing or commercial use of the artwork	*– I will claim it.*
Sensitive content	Sensitive content (3.1%)	Languages containing swear words, fetish, or erotic messages, often sexually explicit fantasy according to the creation	*– I want Rox's thighs wrapped around my head*

Social interaction refers to consumers' positive activities that express support for the creator, or create positive emotional or interpersonal connections. It could also include the code when consumers disclose their fan identities of the original IP revealed from the artworks, such as by providing in-depth discussion on characters or story settings in the original IP.

Dissemination refers to the actions taken by consumers to seek rights for the utilization of current creation. It often involves consumers expressing interest in acquiring these creations for personal or business purposes.

Sensitive content refers to consumers discussing some NSFW content in the community, e.g., imagining the erotic interaction with characters in the creation.

3.4.2 Commenting Practice Classification. Two of the three coders coded another 100 randomly sampled comments to validate their understanding of the codebook, and they achieved substantial agreement (Gwet's AC1 ≥ 70% for each code). After that, they annotated another 700 comments, and the conflicts were solved by the third coder. Eventually, we obtained 1000 annotated comments.

The data was also randomly divided into three distinct sets: training (60%), validation (20%), and test (20%). Five language models were employed for the purpose of predicting the comments category, including BERT-base-uncased [30], Bertweet-base [87], Bertweet-large [87], Bert-base-multilingual-uncased [30], and Multilingual-e5-large-intstruct [112]. Each model was then fine-tuned to predict the categories individually, with the objective of identifying the model that performed best for each dimension. Further details on the performance of the models can be found in Table 5.

To automate the prediction of post comments, the data was categorized into eight categories across five topics using binary classification models. Five deep learning models commonly used for text classification were evaluated to assess their effectiveness in predicting the aforementioned comments categories. Despite the inclusion of 1000 labeled comments per category, as we mentioned above, the dataset exhibited a high degree of imbalance, with some categories being relatively rare (e.g., providing suggestions with only 2%). The imbalance of the data set presented a challenge to the training of the models. To mitigate this problem we have similarly adopted balanced softmax loss, as mentioned above. Furthermore, we utilize a prevalent data augmentation technique, termed Easy Data Augmentation, for categories that are challenging to train (e.g., providing suggestions) [116]. This approach generates a set of augmented data and labels by replacing selected words or phrases from the original data with synonyms or semantic substitutions. The model was trained on the training dataset, evaluated on the validation dataset, and the final performance was assessed using the test dataset.

Table 5. The model performance on F1-score with the test dataset of each comment category (the bold for the best performance). We also report the ratio of each code in the entire predicted dataset.

	Content of Creation		Knowledge exchange		Social interaction		Dissemination	Sensitive
	Judgment	Interpretation	Providing suggestion	Investigation	Peer bonding	Fandom building	Requesting usgage	Sensitive Content
BERT-base	0.842	0.709	0.364	0.500	0.521	0.400	0.483	0.375
Bertweet-base	0.850	0.707	0.444	0.621	0.747	0.333	0.706	0.533
Bertweet-large	0.897	**0.795**	0.444	**0.815**	**0.747**	0.667	0.588	0.615
Bert-base-multilingual	0.850	0.605	0.500	0.571	0.622	0.526	0.417	0.444
Multilingual-e5-large	**0.926**	0.794	**0.727**	0.643	0.701	**0.750**	**0.750**	**0.714**
ratio	28.6%	41.4%	2.45%	6.48%	21.85%	2.83%	5.03%	2.26%

3.4.3 Sentiment Analysis. Besides the theme of the received comments, we also consider the valence of the received comment that presents the overall attitude toward the artwork. We measure the valence of the received comment with VADER (Valence Aware Dictionary and sEntiment Reasoner) [60], an open-sourced[1], lexicon and rule-based sentiment analysis engine, which has

[1]https://github.com/cjhutto/vaderSentiment

been widely adopted for social media sentiment analysis by the CSCW and HCI research community. It first assigns the sentiment indicator i (such as words and emojis) with a numeric $score_i$ (ranging from -4 (most negative) to 4 (most positive)). It then calculates the average compound score by summing individual ones, adjusting the output according to specific rules (such as punctuation amplifiers), and normalizing the result to a range between -1 (most extreme negative) and 1 (most extreme positive).

3.5 Measuring Engagement Changes

We conducted a set of statistical analyses to examine the impact of generative AI in the shared creation and the evolvement of user engagement.

For RQ1, we applied a widely adopted change point detection algorithm, *PELT* [106], to identify when the AIGC starts to surge in the community. This algorithm leverages dynamic programming to decide optimal time series segments where subsequences can be most accurately modeled by different data distributions, i.e., the mean and variance of the time-series distribution change in different time series segments. Following the common practice [106], we assumed a Gaussian distribution for each segment, which can accommodate the monthly variability in the AIGC ratio as depicted in Figure 3b. We set the number of time series segments to two, aiming to identify a single significant change point in the ratio of AIGC and thus distinguish the pre-AIGC prevalence period when the ratio of AIGC is relatively low, and the peri-AIGC prevalence period when the AIGC surges in the community.

For RQ2 and RQ3, we combined interrupted time series (ITS) regression with Bayesian structural time series (BSTS) analysis to quantify the changes in community sharing and commenting behaviors before and during the AIGC prevalence period.

Interrupted time series are designed to evaluate the longitudinal effects of interventions in the absence of randomized controlled groups [72]. It has been widely applied to study social media intervention [62, 101, 105], and herein we used its basic form, segmented linear regression model, to account for the immediate changes of sharing and commenting behaviors in response to the AIGC prevalence, along with trend before and after this intervention. Its simplicity makes it a good starting point for understanding and visualizing how interventions affect trends over time. And then BSTS could address more complex confounding factors, including seasonality.

$$Y_t = \beta_0 + \beta_1 T + \beta_2 D + \beta_3 P + \epsilon_t \tag{1}$$

As in Equation 1, Y_t is the response variables for measurements of community sharing and commenting behaviors; T is the number of months from the beginning of observation; D is the intervention indicator, i.e., whether the prevalence of AIGC has taken place; $P = max(0, T - intervention\_time)$ is the number of months since the prevalence of AIGC. Therefore, β_1, β_2 and β_3 represent the trend before the intervention, the immediate effect of the intervention, and the change of trend since the intervention.

Unlike ITS, BSTS predicts the counterfactual responses and confidence intervals across time under a synthetic control that would have occurred if there had not been the intervention [11]. Compared with ITS, BSTS could further capture non-linear trends and seasonality in the pre-intervention period of the response time-series data, and model a synthetic control in the post-intervention period. By comparing the actual value in post-intervention and the predicted value in the synthetic control, we could estimate the causal effect of the intervention. Here we applied BSTS to each response variables for measurements of community sharing and comment- ing behaviors using the CausalImpact R package [10].

We examine the seasonality of variables in BSTS analysis with iterative STL (seasonal and trend decomposition using LOESS) based on the forecast R package [61]. The algorithm quantifies the strength of seasonality on a scale from 0 to 1, measuring how much variance can be attributed to the seasonal pattern after excluding the overall trend from the time series data [66]. We tested the seasonality at various intervals, including bimonthly, quarterly, four-monthly, semiannual, and annual cycles (2, 3, 4, 6, and 12 months, respectively). The highest seasonality was achieved at the annual level, with an average strength of 0.396. This suggests that, on average, 39.6% of the variation in the time series data (i.e., the ratio of monthly description/comment category) can be attributed to annual seasonality, after decomposing the main trend. Therefore, we set the seasonality as 12 months in the BSTS analysis so that the model can more accurately depict the influence of AIGC prevalence. We recorded the average actual value across data points during the post-intervention period, as well as the average counterfactual value predicted by BSTS. The latter represents the expected outcome if the intervention had not occurred. The relative effect was calculated as the average of the relative differences between the actual and predicted values at each time point. We used the posterior tail-area probability (pp) as an inverse indicator of the likelihood of a causal effect.

For RQ4, we examined how creator's reply behaviors evolve as AIGC becomes more prevalent within the community using logistic regression.

$$\begin{aligned}\text{Reply\_to\_comments}_{ij} &= \beta_0 + \beta_1 \text{AIGC\_ratio}_i + \beta_2 \text{Valence}_j + \beta_3^{\text{T}} \textbf{Categories}_{\textbf{j}} \\ &+ \beta_4 \text{AIGC\_ratio}_i * \text{Valence}_j + \beta_5^{\text{T}} \text{AIGC\_ratio}_i * \textbf{Categories}_{\textbf{j}} \end{aligned} \tag{2}$$

As shown in Equation 2, we modeled whether a creator i replies to a specific comment j on their creation ($\text{Reply\_to\_comments}_{i,j}$), on the prevalence ratio of AIGC at the time the associated creation was shared (AIGC_ratio_i), the sentiment valence of the comment (Valence_j), the categories of comment j listed in Table 4 ($\textbf{Categories}_j$, a vector), and the interaction between the prevalence ratio of AIGC and other independent variables ($\text{AIGC\_ratio}_i * \text{Valence}_j$, $\text{AIGC\_ratio}_i * \textbf{Categories}_{\textbf{j}}$).$\beta_0$ is the intercept term, and β_1, β_2, β_3, β_4, β_5 are the coefficients of variables, where β_3 and β_5 are vectors. Logistic regression analyses were performed separately for human-generated and AI-generated artworks. Table 6 shows the descriptive statistics for independent and dependent variables in RQ4.

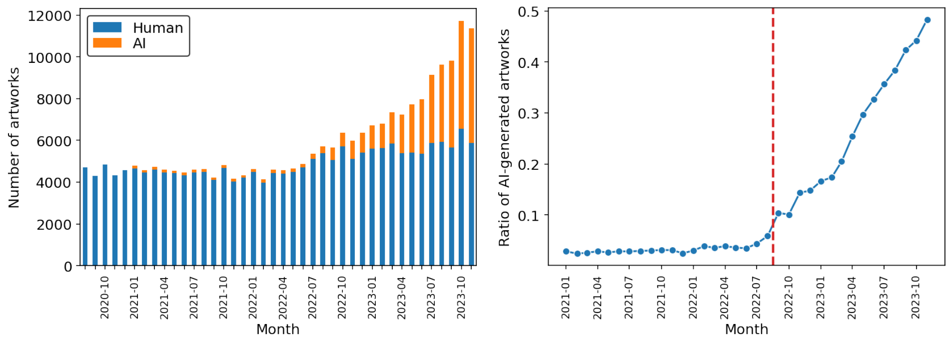
Table 6. Distribution of dependent variables (creator's reply) and independent variables for predicting creator's reply behavior in RQ4. [Added Table]

		Human-created artworks			AI-generated artworks		
	Variables	min/max	mean (std)	median	min/max	mean (std)	median
Received comment	Valence	-1/1	0.318 (0.414)	0.402	-0.995/1	0.407 (0.399)	0.508
	Judgment	0/1	0.284 (0.451)	0	0/1	0.428 (0.495)	0
	Interpretation	0/1	0.427 (0.495)	0	0/1	0.367 (0.482)	0
	Provide suggestion	0/1	0.016 (0.124)	0	0/1	0.013 (0.115)	0
	Investigation	0/1	0.066 (0.249)	0	0/1	0.061 (0.24)	0
	Peer bonding	0/1	0.221 (0.415)	0	0/1	0.18 (0.384)	0
	Fandom building	0/1	0.03 (0.17)	0	0/1	0.014 (0.116)	0
	Dissemination	0/1	0.043 (0.203)	0	0/1	0.028 (0.165)	0
	Sensitive response	0/1	0.022 (0.145)	0	0/1	0.062 (0.241)	0
Community Practice	Monthly AIGC	0.024/0.483	0.136 (0.143)	0.039	0.024/0.483	0.239 (0.159)	0.205
Creator response	is reply	0/1	0.477 (0.499)	0	0/1	0.358 (0.479)	0

4 Result and Analysis

4.1 RQ1. Trend of AI-Generated Artworks in Community

Figure 3a presents the volume of artworks in our sampled dataset aggregated by month. The numbers of human-created artworks were generally stable in the time range, while the numbers



(a) Number of AI-generated and human-created artworks in each month.

(b) Ratio of AI-generated artworks in each month.

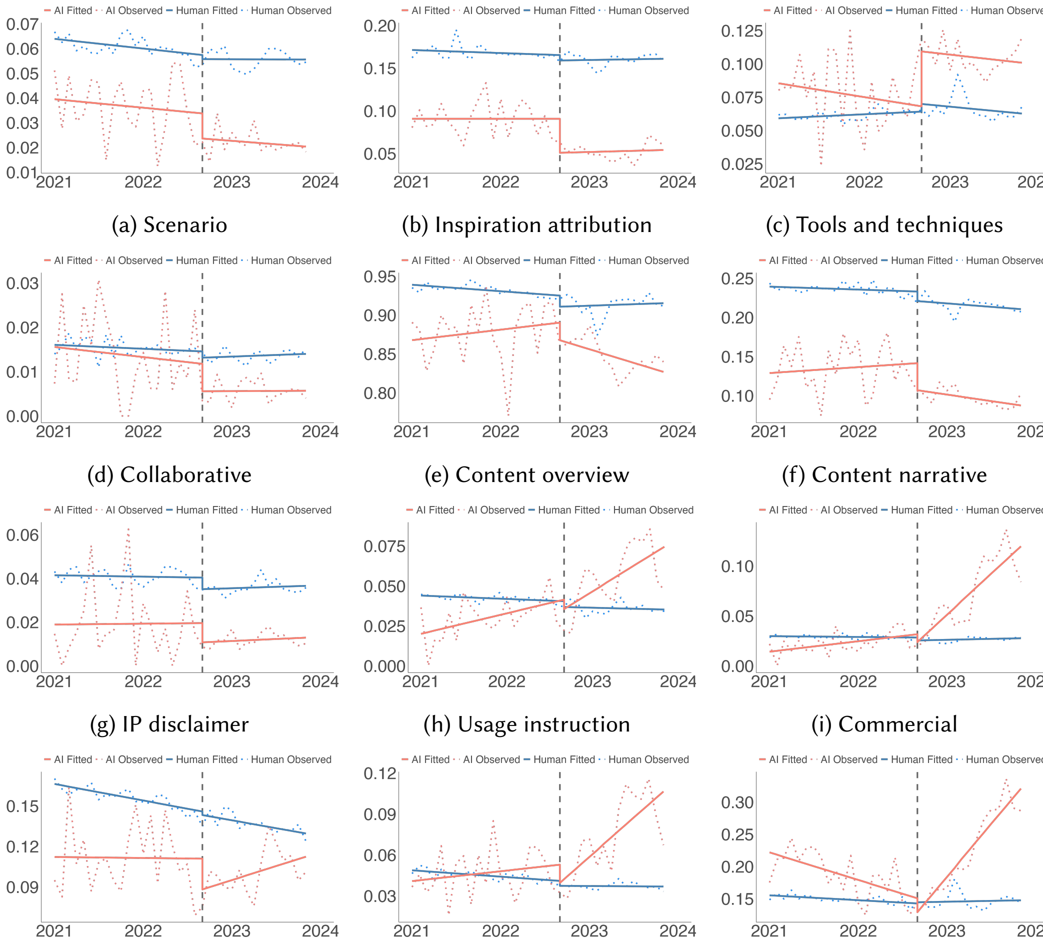
Fig. 3. The trend of AI-generated and human-created artworks in each month.

of AI-adopted artworks increased rapidly and became comparable to the numbers of human-created artworks at the end of 2023. This confirms that the creation process has been transformed significantly due to generative AI techniques.

To capture the transformation of AIGC within the community, we compute the proportion of AI-generated artworks relative to the total number of uploaded artworks (as shown in Figure 3b). We applied the PELT algorithm (as mentioned in Section 3.5) and set the number of time segments into two to identify the optimal change point in the proportion trend. The PELT algorithm iterates all the time points and finds that the best-fitted data is achieved when dividing time segments into two parts: before September 2022, and starting from that month. This indicates a great shift in the mean (and variance) of the AIGC ratio in the community since September 2022 (illustrated by the red vertical line in Figure 3b). Two-sample t-test further suggests a significant increase ($p < 0.001$) in the presence of AI-generated artwork within the community from that point onwards ($M = 0.267, std = 0.129$) than before ($M = 0.033, std = 0.008$). Therefore, we defined the period starting from September 2022 as the AIGC prevalence period, and the period preceding September 2022 as the pre-AIGC prevalence period. Note that September 2022 is also around the time when common text-to-image models, such as Midjourney, Stable Diffusion, and DALL-E 2 become widely accessible, indicating the reliability of the PELT algorithm. In the subsequent sections, we conceptualize the time when AIGC became noticeable in the community as an intervention, and investigate how such intervention (i.e., the prevalence of AIGC) may affect community members' sharing and interaction behaviors.

In RQ1, we confirm the surge of AIGC in the community and identify that salient changes in the creative practices happened around September 2022. Together with the result in Section 3.2, we reveal that many AIGC creators did not disclose their AI usage. Such behavior may bring challenges for community moderation and we discuss the community design implications in Section 5.2.4. Nevertheless, we find that introducing a new creation approach opened the opportunity for the community to grow. Given the dynamics in creation, we then explore how community members (i.e., creators and consumers) engaged with content from different creative processes and how the AIGC surge affected the trend. Addressing these research questions could provide guidance for communities to ensure a good user experience and continue to thrive in the era of AIGC.

4.2 RQ2. Impact of AIGC Prevalence on Artwork Description



(a) Scenario (b) Inspiration attribution (c) Tools and techniques

(d) Collaborative (e) Content overview (f) Content narrative

(g) IP disclaimer (h) Usage instruction (i) Commercial

(j) Socialization (k) Interaction guidance (l) Promotion

Fig. 4. The monthly trend in the ratio of description categories for both human-created and AI-generated artworks. The x-axis represents the time period, while the y-axis shows the ratio of each description category with respect to all human (blue line) or AI artworks (orange line) that month. Dotted lines indicate the observed values and solid lines represent the fitted Interrupted Time Series (ITS) regression models.

4.2.1 Evolvement of creators' description. We first analyzed the impact of AIGC prevalence on the description of human and AI-generated artworks by ITS and BSTS analysis. Overall, human-created artworks show a relatively stable trend in these sharing practices, with no significant changes in the subsequent linear trend ($p > 0.05$ for $\beta_{3,human}$) as revealed by ITS analyis. Meanwhile, relative effects in the BSTS analysis is less than 15% on all dimensions (Table 7).

On the other hand, AI-generated artworks present greater changes in the sharing practices than human-created artworks as AIGC surged. As shown in Figure 4a, 4b, 4e, 4f, AI-generated artworks present a decreasing trend in describing the context of creation and content of creation. The BSTS analysis suggests a negative causal impact of AIGC prevalence on descriptions of GenAI artworks in these categories ($pp < 0.05$), with a decrease of -38.57%, -43.74%, -4.62%, -29.62% on the relative changes of scenario, inspiration attribution, content overview, and content narrative,

Table 7. BSTS analysis of sharing practice in the human and AI-generated artworks. The actual sentiment/theme ratio (denoted as *Actual*) represents the observed monthly average values during the AIGC prevalence period. The counterfactual monthly average values (*Predicted*), estimated using BSTS, indicate what the sentiment/theme ratio would have been in the absence of the intervention (AIGC prevalence). Predicted values are reported with their 95% confidence intervals (95%CI), which is the range that likely contains the true predicted value 95% of the time if sampling is repeated. The relative effect is calculated as the relative differences between actual and predicted values at each time point on average. The 95% confidence intervals of the relative effect is also reported. The posterior tail-area probability (*pp*) is an indicator for the probability of existing causal impact. The lower its value is, the higher chance for the causal impact.

Theme	Code	Post-intervention avg. value			Relative effect (%)		
		Actual	Predicted	95% CI	%Change	95% CI	pp
Human-created artworks							
Context of creation	Scenario	5.56%	5.75%	[4.5%, 6.52%]	-2.43	[-14.72, 23.69]	0.280
	Inspiration attribution	15.99%	16.71%	[15.48%, 17.63%]	-4.16	[-9.28, 3.31]	0.078
Process of creation	Tools and techniques	6.63%	6.32%	[5.38%, 7.45%]	5.55	[-11.02, 23.12]	0.216
	Collaborative information	1.36%	1.51%	[1.3%, 1.68%]	-9.47	[-19.49, 4.68]	0.053
Content of creation	Content overview	91.29%	92.53%	[90.8%, 93.99%]	-1.33	[-2.87, 0.54]	0.060
	Content narrative	21.56%	23.69%	[23.17%, 24.13%]	-8.98	[-10.65, -6.97]	< 0.001
Dissemination of creation	IP disclaimer	3.58%	4.05%	[3.67%, 4.37%]	-11.31	[-18.12, -2.51]	0.019
	Usage instruction	3.6%	4.03%	[3.46%, 4.45%]	-10.4	[-19.15, 4.12]	0.052
	Commercial	2.65%	2.89%	[2.68%, 3.05%]	-8.28	[-12.97, -1.01]	0.021
Community interaction around creation	Socialization	13.63%	14.71%	[12.54%, 16.66%]	-6.87	[-18.18, 8.69]	0.146
	Interaction guidance	3.71%	4.31%	[3.48%, 5.0%]	-13.24	[-25.83, 6.51]	0.057
	Promotion	14.6%	14.45%	[13.18%, 15.49%]	1.2	[-5.73, 10.74]	0.410
AI-generated artworks							
Context of creation	Scenario	2.2%	3.74%	[2.4%, 5.06%]	-38.57	[-56.82, -9.38]	0.019
	Inspiration attribution	5.24%	9.54%	[7.58%, 11.31%]	-43.74	[-53.62, -30.8]	0.005
Process of creation	Tools and techniques	10.51%	7.96%	[5.44%, 10.25%]	45.15	[2.47, 93.14]	0.020
	Collaborative information	0.56%	1.14%	[-0.01%, 2.2%]	25.98	[-132.33, 82.92]	0.103
Content of creation	Content overview	84.72%	88.92%	[84.86%, 95.27%]	-4.62	[-11.08, -0.16]	0.024
	Content narrative	9.71%	13.99%	[11.16%, 17.29%]	-29.62	[-43.82, -12.92]	0.006
Dissemination of creation	IP disclaimer	1.18%	2.16%	[0.39%, 3.82%]	-38.32	[-75.66, 62.09]	0.084
	Usage instruction	5.5%	3.18%	[-0.06%, 5.86%]	64.81	[-307.2, 503.02]	0.038
	Commercial	7.16%	2.51%	[0.98%, 4.48%]	670.96	[49.55, 546.51]	0.001
Community interaction around creation	Socialization	10.02%	10.88%	[7.37%,13.39%]	-0.05	[-25.24, 34.75]	0.193
	Interaction guidance	7.29%	4.61%	[2.5%,6.51%]	71.46	[10.13, 169.12]	0.009
	Promotion	22.49%	14.12%	[3.86%, 22.73%]	70.29	[-4.59, 402.22]	0.028

respectively. Meanwhile, human-created artworks possess a comparatively stable trend on these categories, while only content narrative shows a significant decrease (relative change$_{human}$ = -8.98%, $pp_{human} < 0.001$) as AIGC became prevalent.

Figure 4g demonstrates that the practice of revealing IP issues maintains a relatively low level for AI-generated artworks. A sudden drop ($\beta_{2,human} < 0$) in such behavior exists for human-created artworks, and maintains at a similar level as AIGC surges. The BSTS analysis further indicates that the widespread AIGC brings a negative causal impact (relative effect$_{human}$ = -11.31%, $pp = 0.019$) on creators' practice in disclaiming IP issues in the human-created artworks. Meanwhile, Figure 4c depicts a sudden increase ($\beta_{2,AI} > 0$) in announcing the tools and techniques for AI-generated artworks. Similarly, BSTS analysis confirms a positive causal impact (relative effect$_{AI}$ = 45.15%, $pp = 0.02$) of AIGC prevalence on descriptions of tools and techniques for GenAI artworks. These findings suggest that the change in the creation approach is reshaping the community norms around the creation process and copyright issues.

Figure 4i depicts a significant subsequent increasing trend ($\beta_{3,AI} > 0$) in the commercial information for AI-generated artworks, while a significant sudden drop ($\beta_{2,human} < 0$) for human-created artworks. The BSTS analysis suggests commercial practices culminate in the wave of generative AI for those sharing AI-generated artworks (relative effect: 670.96%, $pp = 0.001$), while an opposite trend exists for human-created artworks (relative effect: −8.28%, $pp = 0.021$). This might indicate that individuals who initially joined the community for commercial purposes may be shifting towards using AI tools for their creations. Similarly, Figure 4l demonstrates a significant upward trend ($\beta_{3,AI} > 0$) for creators sharing AI-generated artworks to promote themselves. This trend is accompanied by a substantial positive causal impact (relative effect$_{AI}$: 70.29%, $pp = 0.028$) due to the popularity of AIGC. These findings suggest that the rise of generative AI tools motivates an increased commercial tendency for creators of GenAI artworks, and there is an increasing trend for these creators to direct audiences to their other works.

Figure 4j and Figure 4k illustrate that for human-created artworks, the practice of mentioning themes related to socialization and interaction guidance is on a relatively steady decline. On the other hand, GenAI artworks have seen an accelerated increase ($\beta_{3,AI} > 0$) in the theme of interaction guidance since AIGC prevalence, accompanied by a significant positive causal effect (relative effect$_{AI}$: 71.46%, $pp = 0.009$).

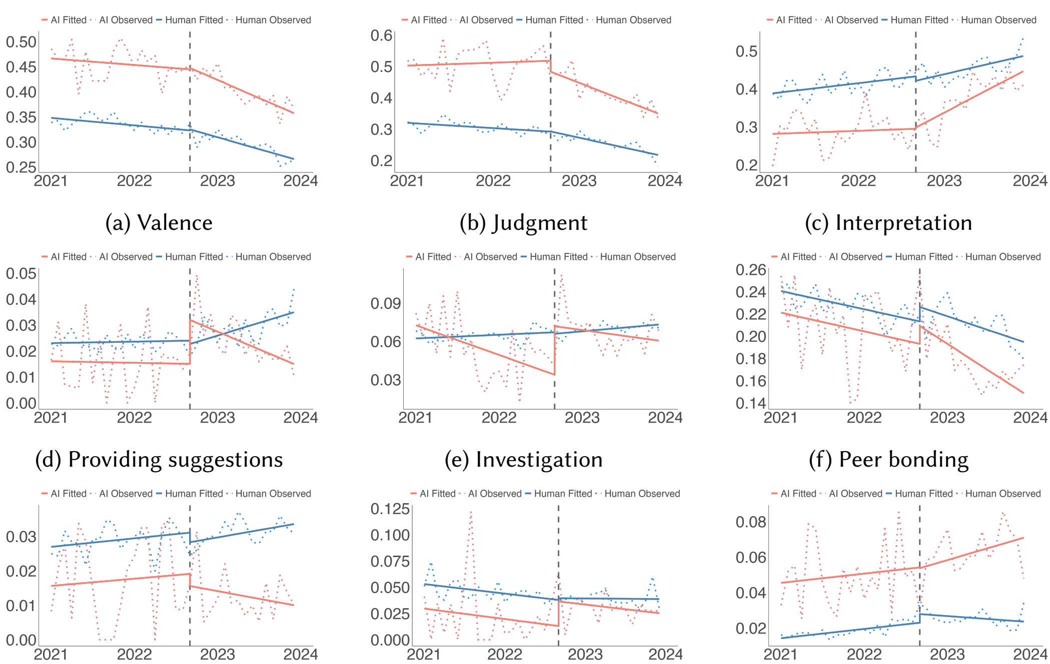
4.2.2 Comparing description during AIGC prevalence period. We then revealed how the practice of describing the artworks during the AIGC prevalence period (since September 2022) vary between human and AI-generated artworks. We set the former as the control group and the latter as the experimental group, and employed the chi-squared test [97] to compare the two groups. We also calculated the Odds Ratio (OR), defined as the percentage of the posts that contain the specific code in the experimental group over that in the control group. The value of OR exceeding one stands for a higher percentage of the code in the experimental group than in the control group, and vice versa.

We observe a significantly lower proportion in disclosing the creation context (creation scenario: $OR = 0.38, p < 0.001$, inspiration attribution: $OR = 0.34, p < 0.001$) between AI-generated artworks and human-created artworks. Similarly, AI-generated artworks were associated with less detailed content narrative ($OR = 0.43, p < 0.001$) than human-created artworks. While creators of AI-generated artworks were more transparent in the adopted tools ($OR = 1.58, p < 0.001$) and techniques than their counterparts, they were less likely to contain collaborative information ($OR = 0.41, p < 0.001$), indicating the shift in creation practices. Meanwhile, AI-generated artworks were less likely ($OR = 0.33, p < 0.001$) to disclaim IP issues than human-created artworks. We find that AI-generated artworks are associated with a greater tendency to emphasize the dissemination of creation (commercial information: $OR = 3.4, p < 0.001$; usage instruction: $OR = 1.71, p < 0.001$) and community interaction (promotion information: $OR = 1.8, p < 0.001$; interaction guidance: $OR = 2.29, p < 0.001$) than human-created artworks. These findings indicate that human creators of artworks present a higher attachment to their current creation, whereas creators of AI-generated artworks tend to leverage increased productivity for commercial purposes and greater personal exposure.

Summary: Human-created artworks exhibit relatively stable trends in response to the surge of AIGC. They display less copyright awareness and a gradual decrease in socialization as AIGC surges in the community. AI-generated artworks, instead, show a decreasing emphasis on the content of creations but an increasing trend toward commercial and promotion purposes. During the AIGC prevalence period, human-created artworks maintain higher enthusiasm for sharing the context and narrating the content of creation, but show lower interest in commercial use and are less transparent in revealing their tools and techniques than AI-generated artworks. Collectively, these findings suggest that human creators of artworks present a stronger attachment to their current creations, whereas creators of AI-generated artworks tend to leverage increased productivity for commercial and promotion purposes.

In RQ2, we first present the impact of AIGC surge on creators' engagement in sharing their artworks (Section 4.2.1) and then compare differences when these artworks were manifested purely by humans versus with the help of AI. These insights deepen the understanding of the community value (e.g., motivation to share the creation) for different creators, and how such value may evolve. More efforts in community moderation may be required as potential issues arise, such as low awareness of copyright in AIGC. We share our insights on these findings in Section 5.1.1 and 5.1.3, and discuss design implications for communities under the trend in Section 5.2.1 and 5.2.3. In Section 4.3, we shift the focus to consumers and explore the evolvement of their community value in an influx of AIGC.

4.3 RQ3. Impact of AIGC Prevalence on Consumer Behaviors



(a) Valence (b) Judgment (c) Interpretation

(d) Providing suggestions (e) Investigation (f) Peer bonding

(g) Fandom building (h) Request usage (i) Sensitive content

Fig. 5. The monthly trend in the ratio of comment categories for both human-created and AI-generated artworks. The x-axis represents the time period, while the y-axis shows the ratio of each comment category with respect to all human (blue line) or AI artworks (orange line) that month. Dotted lines indicate the observed values and solid lines represent the fitted Interrupted Time Series (ITS) regression models.

4.3.1 Evolvement of consumers' comments. Similarly to RQ2, we combined the ITS and BSTS to investigate the evolvement of commenting behaviors. We examined the evolvement of sentiment valence (measured by VADER [60], a widely adopted tool for social media data sentiment analysis) and the content category of comments (through our fine-tuned classifiers).

Table 8. BSTS analysis of commenting practice for human and AI-generated artworks. The actual sentiment/theme ratio (*Actual*) represents the observed monthly average values during the AIGC prevalence period. The counterfactual monthly average values (*Predicted*), estimated using BSTS, indicate what the sentiment/theme ratio would have been in the absence of the intervention (AIGC prevalence). Predicted values are reported with their 95% confidence intervals (95%CI), which is the range that likely contains the true predicted value 95% of the time if sampling is repeated. The relative effect is calculated as the relative differences between actual and predicted values at each time point on average. The 95% confidence intervals of the relative effect is also reported. The posterior tail-area probability (*pp*) is an indicator for the probability of existing causal impact. The lower its value is, the higher chance for the causal impact.

Theme	Code	Post-intervention avg. value			Relative effect (%)		
		Actual	Predicted	95% CI	%Change	95% CI	pp
Human-created artworks							
Sentiment	Valence	29.52%	32.23%	[28.33%, 36.17%]	-8.09	[-18.38, 4.2]	0.071
Content of creation	Interpretation	45.37%	41.91%	[34.77%, 49.28%]	8.99	[-7.94, 30.48]	0.117
	Judgment	25.45%	29.24%	[23.63%, 34.81%]	-12.18	[-26.9, 7.69]	0.077
Knowledge exchange	Providing suggestions	1.75%	1.45%	[1.26%, 1.74%]	21.72	[0.37, 38.41]	0.023
	Investigation	6.94%	6.71%	[6.0%, 7.91%]	4.07	[-12.26, 15.62]	0.225
Social Interaction	Peer bonding	21.04%	21.97%	[18.73%, 25.0%]	-3.72	[-15.84, 12.34]	0.231
	Fandom building	3.09%	3.0%	[2.37%, 3.83%]	4.65	[-19.29, 30.61]	0.313
Dissemination	Requesting usage	3.9%	4.37%	[2.47%, 5.95%]	-7.25	[-34.52, 57.61]	0.226
Sensitive response	Sensitive response	2.57%	2.36%	[1.46%, 3.43%]	14.48	[-25.1, 75.69]	0.302
AI-generated artworks							
Sentiment	Valence	40.21%	46.08%	[42.9%,49.26%]	-12.6	[-18.37,-6.27]	0.008
Content of creation	Interpretation	37.2%	28.29%	[13.82%, 42.63%]	42.71	[-12.78, 168.52]	0.104
	Judgment	41.59%	52.76%	[46.26%, 61.81%]	-20.78	[-32.71, -10.1]	0.006
Knowledge exchange	Providing suggestions	1.52%	0.82%	[-0.44%, 2.15%]	289.06	[-927.59, 1140.78]	0.095
	Investigation	6.61%	4.4%	[-0.78%, 10.2%]	32.74	[-524.26, 710.63]	0.168
Social Interaction	Peer bonding	17.89%	19.55%	[14.96%, 22.88%]	-9.69	[-21.9, 19.46]	0.113
	Fandom building	1.28%	1.54%	[-0.2%, 3.55%]	-251.52	[-253.33, 235.42]	0.313
Dissemination	Requesting usage	3.08%	0.83%	[-5.96%, 5.09%]	65.19	[-1474.81, 1354.21]	0.117
Sensitive response	Sensitive response	6.23%	4.87%	[3.23%, 7.0%]	34.71	[-11.99, 90.6]	0.061

Figure 5a shows that the valence of comments towards human and AI-generated artworks declines more steeply ($\beta_{3,human}, \beta_{3,AI} < 0$) with the usage of AIGC growing in the platform. The BSTS analysis further demonstrates that the widespread of generative AI tools had a negative causal impact (relative effect$_{AI}$: $-12.6\%, pp_{AI} = 0.008$) on comment valence for GenAI artworks.

We then explore the evolvement on the content creation of comments. Several similar trends exist for human and AI-generated artworks. As depicted in Figure 5b, consumers present a sharper decrease ($\beta_{3,human}, \beta_{3,AI} < 0$) in judging the content for both human and AI-generated artworks as AIGC rises in the community. The BSTS analysis further demonstrates the negative causal impact (relative effect$_{AI}$: $-20.78\%, pp_{AI} = 0.006$) of AIGC prevalence on consumers' practices in judging AI-generated artworks. Figure 5c shows that comments containing content interpretation keep increasing for both human and AI-generated artworks. We also observe that comments for fandom building maintain a similar level (no significant β_1, β_2, or β_3) for both human and AI-generated artworks (Figure 5g).

However, nuances exist between the evolvement of human and AI-generated artworks. For AI-generated artworks, Figure 5d shows a downward subsequent trend ($\beta_{3,AI} < 0$) of consumers' practices in providing suggestions. For human-created artworks, the BSTS analysis suggests that the AIGC prevalence encouraged (relative effect$_{human}$: 21.72%, $pp = 0.023$) creators to provide suggestions for these artworks. Moreover, Figure 5e presents a sudden increase in investigating the creation of AI-generated artworks ($\beta_{2,AI} > 0$) as AIGC starts to become prevalent in the community. Figure 5h depicts that consumers' comments for requesting the usage of AI-generated artworks maintain at a similar level as AIGC rises (no significant β_1, β_2, or β_3), while the usage request for human-created ones keeps decreasing ($\beta_1 < 0$). Figure 5f demonstrates that for human-created artworks, the received comments for peer bonding keep going down at a significant level ($\beta_1 < 0$).

4.3.2 Comparing Comments during AIGC prevalence period. We further compared consumers' valence towards human and AI-generated artworks during the AIGC prevalence period through t-test. Consumers presented significantly higher ($p < 0.001$) valence toward the AI-generated artworks than human-created artwork.

We then compared the consumers' commenting focus during the AIGC prevalence period between the human and AI-generated artworks through the Chi-squared test and calculate the odds ratio (AI-generated over human-created). While consumers are more likely ($OR = 1.58, p < 0.001$) to judge the content of AI-generated artworks than human-created ones, they are less likely ($OR = 0.86, p < 0.001$) to interpret the content of creation. We also observe that AI-generated artworks are less likely to receive comments surrounding creative feedback, no matter whether providing suggestions ($OR = 0.84, p = 0.047$) or investigating the creation ($OR = 0.92, p = 0.026$). Meanwhile, AI-generated artworks present a lower ($OR = 0.76, p < 0.001$) association of soliciting usage from consumers than human-created artworks. Consumers also present a relatively lower practice in socialization, no matter for direct peer bonding with the creator ($OR = 0.82, p < 0.001$), or for fandom building in the community ($OR = 0.4, p < 0.001$). Finally, consumers present significantly higher frequency ($OR = 2.6, p < 0.001$) in leaving sensitive responses toward AI-generated creations than human-created ones.

Summary: AI-generated artworks receive comments with higher valence and more sensitive responses compared to those of human-created artworks. Human-created artworks are more likely to receive comments for creation feedback, as well as messages aimed at engaging in peer bonding and requesting usage than AI-generated artworks. As AIGC surges, both types of creators experience a drop in sentiment valence and judgments of creation. However, consumers continue to increase comments containing content interpretation for both human and AI-generated artworks. Moreover, human creators tend to receive more suggestions, while AI creators present an opposite trend with the growing usage of AIGC in the community. Additionally, human creators receive decreasing comments aimed at requesting usage and peer bonding.

Answers to RQ3 illustrate that, similar to creators (RQ2), the rise of AIGC affects consumers' engagement patterns with a significant difference toward AI- versus human-generated artworks. We provide deeper discussion in Section 5.1.1. Creators replying to comments on their shared creation, is a signal of engaging in the community [17, 48, 124]. Therefore, we further investigate how creators may appreciate the received comments in RQ4. Such knowledge can complement RQ2 and provide another aspect of creators' engagement beyond content sharing. It also helps to interpret how changes in consumers' engagement (RQ3) may subsequently affect the community ecosystem.

Table 9. Logistic regression for creators' reply behaviors.

	Model 1: Human			Model 2: AI		
	Coefficient	SE	p-value	Coefficient	SE	p-value
Valence	0.1042	0.017	<0.001	0.3595	0.095	<0.001
Judgment	0.2393	0.016	<0.001	0.2788	0.082	0.001
Interpretation	0.6023	0.015	<0.001	0.6225	0.083	<0.001
Suggestion	0.0812	0.051	0.113	0.2839	0.3	0.345
Investigation	0.8938	0.026	<0.001	0.8912	0.138	<0.001
Peer bonding	0.0691	0.016	<0.001	0.1246	0.089	0.16
Fandom building	-0.1042	0.037	0.005	0.0034	0.256	0.989
Dissemination	0.4399	0.031	<0.001	0.9766	0.209	<0.001
Sensitive	-0.4316	0.044	<0.001	-0.7294	0.158	<0.001
AIGC ratio	0.0923	0.069	0.178	-0.1557	0.276	0.573
AIGC ratio × Valence	0.0546	0.086	0.524	-0.7865	0.329	0.017
AIGC ratio × Judgment	-0.5051	0.084	<0.001	-0.8732	0.292	0.003
AIGC ratio × Interpretation	-0.3128	0.075	<0.001	-0.686	0.29	0.018
AIGC ratio × Suggestion	0.1511	0.245	0.537	0.3827	1.039	0.713
AIGC ratio × Investigation	-0.2781	0.13	0.032	0.9959	0.483	0.039
AIGC ratio × Peer bonding	0.0752	0.084	0.372	0.3787	0.323	0.242
AIGC ratio × Fandom building	-0.4071	0.184	0.027	1.5768	0.912	0.084
AIGC ratio × Dissemination	0.0513	0.164	0.754	-0.0179	0.74	0.981
AIGC ratio × Sensitive	-0.1541	0.224	0.491	1.3962	0.522	0.007
Intercept	-0.5081	0.014	<0.001	-0.9571	0.079	<0.001

4.4 RQ4. Impact of AIGC Prevalence on Creator Reply Behaviors

We then investigated whether and how the creators' interaction behaviors with consumers (whether the creator replies to a comment) evolve as AIGC becomes prevalent in the community using logistic regression. The independent variables include consumers' comments (their sentiment and categories), the monthly AIGC ratio when creators posted the creation, and their interaction terms. We list the results of the logistic regression model for human-created artworks (Model 1) and AI-generated artworks (Model 2) in Table 9.

We observe creators of both human and AI-generated artworks exhibit similar reactions toward the received feedbacks as critique and fandom-oriented creative communities. Specifically, commenting on the content of creation (judgment ($\beta_{human} = 0.239, p < 0.001$; $\beta_{AI} = 0.279, p < 0.001$) and interpretation ($\beta_{human} = 0.602, p < 0.001$; $\beta_{AI} = 0.623, p < 0.001$)) and raising questions toward the creation ($\beta_{human} = 0.894, p < 0.001$; $\beta_{AI} = 0.891, p < 0.001$) is positively correlated with the creators' (no matter of sharing human or AI-generated artworks) reply behavior. The increased likelihood of replying to such comments highlights the importance of sensemaking social interactions in the creation process for both human and AI creators [73]. Similar to findings in [23, 48], creators for both creation approaches are more likely to reply when receiving comments with higher valence ($\beta_{human} = 0.104, p < 0.001$; $\beta_{AI} = 0.360, p < 0.001$). For creators sharing human-created artworks, they are more likely to engage with the comments for peer bonding ($\beta_{human} = 0.069, p < 0.001$). This is consistent with the benefits of positive social support to creators [17, 23].

Creators for artwork sharing also present some unique behaviors than other communities. Creators are more likely to engage in social interaction when consumers express interest in using the creation ($\beta_{human} = 0.044, p < 0.001$; $\beta_{AI} = 0.977, p < 0.001$), potentially stemming from a sense of accomplishment due to the recognition of their creative output or the heightened awareness of copyrights issues in online creative communities [40]. However, we observe that providing design feedbacks is not particularly effective (suggestion, $p > 0.05$ for both human and AI-generated artworks) in engaging creators to reply, demonstrating the difference between DeviantArt and other creative communities for critique exchange in prior studies [18]. Creators of both human and AI-generated artworks are less likely to reply to sensitive content ($\beta_{human} = -0.432, p < 0.001$; $\beta_{AI} = -0.729, p < 0.001$), suggesting the potentially offensive experience for creators when receiving such comments (e.g., often associated with erotic information) or the reluctance to "disrupt" the personal fantasy of their audience. And interaction for fandom building under human-created artworks is associated with a lower chance of creators' replies ($\beta_{human} = -0.104, p = 0.005$). This may be explained by a sense of being challenged when compared with the creation setting in the original IP or that the lengthy text of fan discussion discourages creators from following.

The interaction terms in Model 1 and Model 2 further reveal the evolvement of how creators' engage with consumers. First, we find the positive effect of discussing content of creation get suppressed (AIGC ratio × judgment: $\beta_{human} = -0.505, p < 0.001$, $\beta_{AI} = -0.873, p = 0.003$; AIGC ratio × interpretation: $\beta_{human} = -0.313, p < 0.001$, $\beta_{AI} = -0.686, p = 0.018$) as AIGC surges, indicating creators are decreasing their interest in discussing content of creation with consumers in such a trend.

We also figure out the nuances of reply behaviors for artworks created in different approaches. Creators of AI-generated artworks show less engagement in interacting with comments of high valence as AIGC becomes popular ($\beta_{AI} = -0.787, p = 0.017$), suggesting these creators might possess more emotional detachment from their creative output as generative AI tools become more accessible and powerful. As AIGC becomes more widespread, creators' willingness to respond to questions was hindered ($\beta_{human} = -0.278, p = 0.032$) for human-created artworks, while an opposite trend exists for AI-generated artworks ($\beta_{AI} = 0.996, p = 0.039$). This might be due to that the prevalence of AIGC has heightened people's risk perceptions on AI usage and creators have to clarify and defend their usage in such dialogues [9, 67]. Creators' willingness to participate in the conversation of fandom building under human-created artworks also decreases ($\beta_{human} = -0.407, p = 0.027$) with the growing of AIGC. This may be due to creators striving to maintain the originality of their work by distancing it from fandom characters and their discussion. The negative impact of sensitive content on creators who share AI-generated artworks is reduced ($\beta_{AI} = 1.396, p = 0.007$) with the rise of AIGC. One potential reason might be some creators intentionally leverage generative AI tools to produce NSFW images [16] and would like to engage in such conversation.

Summary: Creators of both human-created and AI-generated artworks exhibit similar positive reactions to comments on content and investigation, which are beneficial to the sensemaking process in creative iteration, although these interactions have dwindled with the prevalence of AIGC. Creators of human-created artworks keep engaging with comments with higher sentiment, as well as those focused on peer bonding and requesting usage. However, these creators present more reluctance to engage in conversations for fandom building as AIGC surges. On the other hand, creators of AI-generated artworks are triggered less by comments in high valence or conversation surrounding the content of the creation, and emphasize more on answering questions with the widespread of AIGC. Both types of creators are less likely to respond to sensitive content, although this resistance is diminishing among AI creators with the rise of AIGC.

These findings demonstrate that community interaction matters for creators with different creative practices, and the relative effectiveness could evolve as AIGC arises in the community. Together with findings in RQ3, we discuss the potential impact of the evolving comments to the community ecosystem in Section 5.1.2. We share our insights on leveraging comments as the design materials to engage community members in Section 5.2.2.

5 Discussion

In this section, we discuss the main findings and propose design implications for the online creative community under the wave of AIGC.

5.1 Key Findings

5.1.1 Heterogeneity of engagement patterns and evolvement between human and AI-generated artworks. We observe that creators and consumers of AI-generated artworks engage with the community in ways different from those of human-created artworks. In Section 4.2.2, we find AI-generated artworks contain more commercial and promotional information. However, they place less emphasis on the context of creation and detailed narrative of the content during the generative AI prevalence period. Figure 4i suggests a rapid increase in commercial purposes expressed in AI-generated artworks, while a slight decrease trend exists for human-created ones. This may indicate that generative AI tools could open up new commercial opportunities for artists by accelerating the creation process and reducing manual efforts [20, 63]. Figure 4a, 4b, 4e, 4f demonstrates the salient decreasing trend of AI-generated artworks in mentioning the context and content of creation, while Figure 4l presents their growing in guiding consumers to other creations as generative AI tools become widespread. These trends are not prominent in human-made artworks. Besides, Model 2 in Table 9 suggests that the positive effect of sentiment valence on engaging creators of AI-generated artworks in replying diminishes as AIGC surges. In contrast, human-created artworks present less fluctuation in these dimensions despite the rise of AIGC, indicating that creators of human-made artworks maintain their motivation for personal expression and emotional input in their creations. Such differences might be attributed to the automated and algorithmic nature of AIGC, which can lead to a detachment from traditional creative processes that involve personal experiences and storytelling [70].

We also observe that across posts and comments, practices toward AI-generated content often exhibit greater variance than those on human-created ones. From the creator's perspective, this might be explained by Rogers' Diffusion of Innovations Theory [100]. Given the emerging generative AI techniques, the attracted AI creators could be divided into different cohorts, such as innovators, early adopters, and the early majority. Different user cohorts may have slightly distinct motivations to participate in the community [2, 47, 83], highlighting the importance of moderating how creators engage in the community as AIGC adoption increases. On the other hand, the novelty effect [71] may explain consumers' greater changes in engagement patterns toward generative AI artworks. Consumers may appreciate the high quality of AI art when they initially appeared, but then lack interest in engaging with them after such creation overwhelms the community. Collectively, these findings indicate different engagement patterns surrounding creations manifested in different fashions and patterns concerning AI-generated artworks show greater variance over time. We encourage future studies to explore the variation in creators' engagement patterns through both quantitative analysis and qualitative interviews to investigate the evolving community value for different cohorts.

5.1.2 Potential negative impact of AIGC surge on creators without using generative AI tools. Model 1 in Table 9 demonstrates the positive effect of sentiment valence, and receiving comments in the categories of creation content, investigation, peer bonding, and dissemination in engaging creators sharing human-created artworks. However, it also suggests that the effectiveness of receiving comments in the categories of judgment, interpretation, and investigation may diminish as AIGC becomes more common, indicating it is increasingly challenging to engage these creators.

Meanwhile, although the positive effects of sentiment, peer bonding, and requesting usage remain relatively stable as AIGC increases, Figure 5a, 5f, 5h demonstrate the decrease of these interactions from consumers. One potential reason might be that as generative AI tools continue to develop, consumers' acceptance of AI as serious artists may rise and the preconceived preference for human-created artworks may diminish. Another possibility is that consumers' commenting behaviors have been influenced by the description of the human-created artworks, as Figure 4i, 4j show a decline in these practices in creators' descriptions. Future qualitative studies could explore why consumers present such change when commenting on human-created artworks and why the effectiveness of certain social interactions evolved in the era of AIGC.

5.1.3 Potential challenges for community moderation in the era of AIGC. We confirm that the rise of AIGC may bring challenges for moderators to regulate online creative communities [80]. We raise two potential risks revealed from our findings.

In Section 4.2.2 we observe that AI-generated artworks emphasize less on IP issues than human-created ones during the AIGC prevalence period. One explanation might be that AI-generated artworks could blur the lines of the traditional definition of copyrights, leading to confusion and uncertainty among creators and moderators regarding IP issues [63]. Figure 4g also demonstrates the awareness of artworks' IP issues in human-created artworks dropped from the pre-AIGC prevalence period to the AIGC prevalence period in the community. This may indicate the community norm in copyright could be affected by the rise of generative AI.

In Section 4.3.2, we observe that AI-generated artworks tend to attract more sensitive content than those created by humans during the AIGC prevalence period. According to Model 1 and Model 2 in Table 9, although creators generally engage less frequently with sensitive comments, those using generative AI tools become less reluctant to respond to sensitive content as the AIGC ratio increases. This shift may be due to creators intentionally leveraging generative AI tools to produce NSFW images to cater to consumers and would like to engage in such conversation [16]. Community moderators should evaluate whether the increasing mutual interactions between creators and consumers, driven by the rise in generative AI usage, align with the community's values. This trend could potentially lead to content homogeneity issues within the community.

5.2 Design Implication

5.2.1 Enhancing engagement of users in light of the popularity of AIGC. One salient contribution of this work is that we show generative AI is influencing user engagement (such as sharing, commenting, and reply behaviors) in the online creative community and its influence is ever-growing. From the perspective of platform moderators, there is a need to reevaluate the platform's role in keeping members engaged given the dynamic shifts in this AIGC era [80, 84]. The findings emphasize the importance of incorporating new factors, such as the community-level AIGC popularity, to engage community members. The platform could integrate the AIGC signal, such as the community macro-level practice and user micro-level interactions, into its recommender system, ensuring that algorithms are updated in alignment with members' current interests [131].

Furthermore, the study shows that user activities around AI-generated and human-generated artworks follow divergent trends. On the one hand, we find that AI art creators increasingly aim to commercialize and promote their artworks – a trend consistent with recent study [117]. To fulfill this emerging need, the platform might design tags like #AI4Commercial and #AI4Promotion to help consumers quickly identify AI-generated artworks intended for commercial use while preserving the community's established norms. On the other hand, the proliferation of AI art has triggered spontaneous reactions among creators who deeply value human creativity and support human-generated artwork (e.g., through increased suggestions for these artworks). This is in line with the desire of human art enthusiasts to differentiate and engage with human-created artworks rather than with AIGC [3, 56]. The platform could design hashtags like #NoAI to increase the visibility of pure human art. Meanwhile, the platform can educate users on the value of engaging with human arts by presenting how human creators diversify creative content and mentor artists in the community. The platform can implement gamification elements like awarding badges to users who consistently support human arts. In addition, organizing events such as human artwork competitions would foster community building and meaningful connections between creators and audiences.

5.2.2 Balancing creator engagement and potential risks in the AIGC surge through commenting. Our analysis in Section 4.4 shows that commenting could serve as a strategy to engage creators. Although the relative effectiveness of different types of comments could change as AIGC surges, sentiment valence, peer bonding, and usage requests have relatively stable, significantly positive effects on the reply behaviors of creators of human-created artworks. These findings align with prior research on feedback exchange and professional development among human creators: 1) positive feedback elevates affective states of creators, encouraging their intrinsic creative motivation [122]; 2) peer bonding strengthens confidence in sharing creations [17]; and 3) usage requests signal professional and social recognition, reinforcing creators' perceived value within the community [22, 83]. This indicates interaction of these natures should be recommended as AIGC becomes prevalent. Nevertheless, the community presents a drop in these themes for human-created artworks. According to the Expectation Confirmation Theory [90], responses that meet creators' expectations are crucial for their satisfaction. Therefore, creators are less likely to be engaged if they fail to receive the desired response. However, creators may not explicitly state their expectations for such interactions, making it more challenging to maintain their involvement and satisfaction [48]. To address this, when the platform detects a creator sharing human-created artworks, it can prompt the creator to specify their desired types of social interaction. The platform can also motivate consumers to respond with more positive sentiment or encourage creators by using advanced NLP techniques to help rephrase their comments. It should be noted that the interaction strategies should be updated dynamically to ensure their effectiveness. Meanwhile, the platform should balance the potential risks of AIGC surge to community interactions. For example, compared with the traditional human-created artworks, we notice that the emerging AIGC tends to trigger more shadow interactions (such as sexual-oriented fantasy) than deep ones (such as discussions around art critiques). Community moderators should monitor the long-term impact of such shadow interactions on the future retention of creators and the establishment of new norms among consumers.

One unique aspect of creative communities is that a creation process often involves multiple stages (such as work-in-progress and complete) [69], and creators can join critique communities, such as those on Reddit [17, 18], to solicit feedback at different creation stages. As AIGC is often in the completion stage, the increase in AIGC may discourage creators from soliciting feedback for ongoing works when early feedback might be most valuable [69]. Meanwhile, since creators can receive immediate responses with the development of multimodal LLMs [77], their expectations regarding community feedback may change. They might expect community feedback to supplement, challenge, or refine suggestions provided by LLMs, and such expectations could vary at different creation stages. Creative platforms could support user needs surrounding the human creative process in this new era by monitoring feedback that engages creators in different creation stages to streamline the exchange of constructive input on shared artworks. Additionally, creative platforms can provide affordances for creators to share their work at any stage of the creation process, making feedback more relevant and tailored to each stage of their work.

5.2.3 Designing community guidelines for generative AI usage. Although generative AI tools could boost productivity in content creation, community moderators should not view them as a panacea for engaging audiences and enriching the creative environment. As AIGC surges, moderators should be aware of its potential influence on community culture. For example, while IP-related issues have already drawn wide discussion of the creative community [38], there has been a decline in disclosing the copyright information in human-created artworks. To protect the vibrancy of the creative environment, the creative community may need to update its guidelines for sharing artworks in response to the trends of AIGC. It would also be worthwhile to investigate how changes in community practices of IP issues may affect the community norms and IP awareness among members as a post-hoc evaluation. Besides, the platform can consider inviting experienced community members to collaboratively edit the content description to ensure that the community norms surrounding creativity remain intact.

5.2.4 Adopting technologies and collaborative curation for recognizing AI-generated artworks. Our findings reveal the variation in the engagement patterns between members surrounding UGC and AIGC. However, through our analysis in Section 4.1, while platforms encourage creators to disclose their AI usage, a substantial number of creators may not do so. This may bring challenges to moderate the community and design customized strategies to engage members. Our study shows the possibility of using AI algorithms to detect AI arts. The platform can train and deploy an AI image classifier with the community data. Meanwhile, the community may also apply a collaborative curation mechanism to identify potential AI arts. Selected community members can indicate their perceived creative practices of a given artwork (i.e., AI-generated or human-created), and such perceptions can be aggregated and shared with broader viewers. Note that platforms need to make the results (by algorithms or peers) transparent to creators. Creators should be allowed to correct errors when they are misclassified to avoid feeling discriminated against.

5.3 Generalizability of Findings

We acknowledge that the impact of AIGC extends beyond the scope of DeviantArt, a platform often used for sharing complete works. First, recent studies have shown that AIGC encourages more participation and posting of artwork on various platforms, whether they are centralized (such as Twitter [16] and Pixiv [117]) or decentralized (often self-governed, e.g., Reddit [84]). Second, the engagement patterns for community members vary when interacting with AI-generated art versus human-created content in broad scenarios. For example, AI creators on both DeviantArt (the focus of this study) and Pixiv [117] are more motivated by monetization. Moreover, similar to our finding that AIGC may pose potential risks to the community (e.g., more comments surrounding AIGC are associated with more sensitive, often sexual content than those on human-created artworks), a large amount of AI-generated artwork on Twitter [16] and Civitai [118] is not safe for work (NSFW). Third, the overall trend of engagement with AIGC content across time can also be generalized to other platforms. For example, the valence of received comments decreases as AIGC becomes more prevalent, a trend that has also been observed in Reddit communities [84].

In addition to how people engage with AI-generated art, the identified potential risks (such as copyright awareness and shadow interaction) triggered by generative AI are not limited to the art domain and can be generalized to other creative communities. For example, there are discussions about a lack of awareness regarding copyright issues for video creation with Sora on

Twitter [130], Reddit [86], and Youtube [58]. Music fandoms are sharing AI covers of popular singers on YouTube [44, 75], leading to debate on copyright infringement issues in the music industry. Developers of non-profit-driven indie games also share concerns that the adoption of generative AI may hinder the uniqueness of their creative products and threaten their career growth [93, 94]. These phenomena suggest that the use of generative AI is often unregulated in its early adoption phases. Stakeholders in other creative communities should not only reflect on the role and value of generative AI in content creation but also engage in proactive measures and community design to address the associated risks.

5.4 Limitations and Future Works

Several limitations exist in this work. First, while we randomly sample substantial artworks over a three-year time range to better reflect the trend on DeviantArt, our collection represents only a portion of the artworks publicly shared on the platform. When analyzing the results obtained from this dataset, researchers should consider the possibility that the artworks may differ from the inherent distribution on the platform. Second, while we consider the seasonality in the engagement trend, we acknowledge that other confounding factors might concurrently affect both the prevalence of AIGC and changes in engagement patterns. For example, the community policy regarding the usage and disclosure of AIGC on DeviantArt has shifted since the rise of generative AI and could influence creators' behaviors in sharing artwork [103]. The changes in artwork descriptions might also be partially attributed to the change in community policy. We encourage future works to unpack such potential entanglement by integrating features at the user level (e.g., creation history) and platform level (e.g., overall activity and community policy). Additionally, ITS and BSTS may not be the most suitable models for capturing the distribution of engagement patterns in our study. We adopted the basic form of ITS, a segmented linear regression model, which has visually discernible parameters but may oversimplify the time series distribution. In contrast, BSTS can capture numerous components of the time series and analyze causal impacts. In this work, we aim to provide the latest insights for the impact of AIGC surge in the online creative community. However, the limited time range of our dataset, owing to the relatively short duration since the recency of AIGC prevalence (less than three years since 2021), slightly compromised the robustness of the findings. We encourage future studies to collect data in a longer time range and examine the longer term impact of AIGC to the community ecosystem.

To extend our research and examine the generalizability of results from our results, future work can investigate the trends of generative AI tools for each type of artifact and the variations in engagement norms within these communities. Researchers could also explore the impact of AIGC in various creative communities, such as for writing, music, and video sharing. Instead of isolating engagement behaviors from the creators, future studies could perform longitudinal analysis to understand the evolution of creators' artistic experiences and community engagement in response to AIGC. Given the explosive growth of generative AI, future research should consider more comprehensive factors that may affect user behaviors and apply our findings to scenarios involving other AI-related interventions or multiple interventions.

6 Conclusion

In this work, we explored the emergence of AIGC in the online creative community in the era of generative AI techniques utilizing a dataset collected from DeviantArt. We confirmed a discernible trend wherein AIGC is gradually replacing UGC within the community. Through open coding, we identified creators' practices in describing the shared artworks and consumers' practices in commenting on the creations. We leveraged deep learning models to classify the posts and comments in the entire dataset. Furthermore, we explored the impact of AIGC prevalence on user engagement (i.e., creators' descriptions in their shared artworks, consumers' comments, and creators' replies), shedding light on the evolving nature of the creative community in the era of AIGC.

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References

[1] AI@Meta. 2024. Llama 3 Model Card. (2024). https://github.com/meta-llama/llama3/blob/main/MODEL_CARD.md
[2] Alkim Almila Akdag Salah and Albert Ali Salah. 2013. Flow of innovation in deviantArt: following artists on an online social network site. *Mind & Society* 12, 1 (2013), 137–149.
[3] Safinah Ali and Cynthia Breazeal. 2023. Studying Artist Sentiments around AI-generated Artwork. *arXiv preprint arXiv:2311.13725* (2023).
[4] Hangbo Bao, Li Dong, Songhao Piao, and Furu Wei. 2021. Beit: Bert pre-training of image transformers. *arXiv preprint arXiv:2106.08254* (2021).
[5] Kevin Bauer, Ekaterina Jussupow, Rebecca Heigl, Benjamin Vogt, and Oliver Hinz. 2024. All Just in Your Head? Unraveling the Side Effects of Generative AI Disclosure in Creative Task. *SSRN Electronic Journal* (2024).
[6] Rahime Belen Saglam, Jason R. C. Nurse, and Duncan Hodges. 2021. Privacy Concerns in Chatbot Interactions: When to Trust and When to Worry. In *HCI International 2021 - Posters*, Constantine Stephanidis, Margherita Antona, and Stavroula Ntoa (Eds.). Springer International Publishing, Cham, 391–399.
[7] Weizhen Bian, Yijin Song, Nianzhen Gu, Tin Yan Chan, Tsz To Lo, Tsun Sun Li, King Chak Wong, Wei Xue, and Roberto Alonso Trillo. 2023. MoMusic: A Motion-Driven Human-AI Collaborative Music Composition and Performing System. In *AAAI Conference on Artificial Intelligence*.
[8] Volker Bilgram and Felix Laarmann. 2023. Accelerating Innovation With Generative AI: AI-Augmented Digital Prototyping and Innovation Methods. *IEEE Engineering Management Review* 51, 2 (2023), 18–25. https://doi.org/10.1109/EMR.2023.3272799
[9] Charlotte Bird. 2024. Artists and AI: Creative Interactions and Tensions. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI EA '24)*. Association for Computing Machinery, New York, NY, USA, Article 49, 6 pages. https://doi.org/10.1145/3613905.3651041
[10] Kay H. Brodersen, Florian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2017. Package CausalImpact. R package version 1.3.0.
[11] Kay Henning Brodersen, Fabian Lee Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. Inferring causal impact using Bayesian structural time-series models. *The Annals of Applied Statistics* 9 (2015), 247–274.
[12] Gordon Burtch, Dokyun Lee, and Zhichen Chen. 2024. The consequences of generative AI for online knowledge communities. *Scientific Reports* 14, 1 (2024), 10413.
[13] Yihan Cao, Siyu Li, Yixin Liu, Zhiling Yan, Yutong Dai, Philip S Yu, and Lichao Sun. 2023. A comprehensive survey of ai-generated content (aigc): A history of generative ai from gan to chatgpt. *arXiv preprint arXiv:2303.04226* (2023).
[14] Jackie Chan, Aditi Atreyasa, Stevie Chancellor, and Eshwar Chandrasekharan. 2022. Community Resilience: Quantifying the Disruptive Effects of Sudden Spikes in Activity within Online Communities. In *Proceedings of the ACM Conference Extended Abstracts on Human Factors in Computing Systems*. ACM, New York, NY, USA, Article 339, 8 pages.
[15] Gillian Chen and Lillio Mok. 2021. Characterizing growth and decline in online ux communities. In *Extended abstracts of the 2021 CHI conference on human factors in computing systems*. 1–7.
[16] Yiqun T. Chen and James Zou. 2023. TWIGMA: A dataset of AI-Generated Images with Metadata From Twitter. In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*.
[17] Ruijia Cheng and Jenna Frens. 2022. Feedback Exchange and Online Affinity: A Case Study of Online Fanfiction Writers. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW2 (2022), 1–29.
[18] Ruijia Cheng, Ziwen Zeng, Maysnow Liu, and Steven Dow. 2020. Critique me: exploring how creators publicly request feedback in an online critique community. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2 (2020), 1–24.
[19] Peggy Chi, Nathan Frey, Katrina Panovich, and Irfan Essa. 2021. Automatic Instructional Video Creation from a Markdown-Formatted Tutorial. In *The 34th Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '21)*. Association for Computing Machinery, New York, NY, USA, 677–690. https://doi.org/10.1145/3472749.3474778

[20] Michael Chui, Eric Hazan, Roger Roberts, Alex Singla, and Kate Smaje. 2023. The economic potential of generative AI. (2023).

[21] John Joon Young Chung, Wooseok Kim, Kang Min Yoo, Hwaran Lee, Eytan Adar, and Minsuk Chang. 2022. TaleBrush: Sketching Stories with Generative Pretrained Language Models. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 209, 19 pages. https://doi.org/10.1145/3491102.3501819

[22] Eric Cook, Stephanie D Teasley, and Mark S Ackerman. 2009. Contribution, commercialization & audience: understanding participation in an online creative community. In *Proceedings of the 2009 ACM International Conference on Supporting Group Work*. 41–50.

[23] Patrick A Crain and Brian P Bailey. 2017. Share once or share often? Exploring how designers approach iteration in a large online community. In *Proceedings of the 2017 ACM SIGCHI Conference on Creativity and Cognition*. 80–92.

[24] Richard Lee Davis, Thiemo Wambsganss, Wei Jiang, Kevin Gonyop Kim, Tanja Käser, and Pierre Dillenbourg. 2024. Fashioning Creative Expertise with Generative AI: Graphical Interfaces for Design Space Exploration Better Support Ideation Than Text Prompts. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 167, 26 pages. https://doi.org/10.1145/3613904.3642908

[25] O Demirci, J Hannane, and X Zhu. 2023. Who Is AI Replacing? The Impact of Genera-tive AI on Online Freelancing Platforms.

[26] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. 2009. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*. Ieee, 248–255.

[27] DeviantArt. 2022. DeviantArt Platform. https://www.deviantart.com/. Retrieved on Jan 1, 2024.

[28] DeviantArt. 2022. New Label Requirement for AI Artwork. https://www.deviantart.com/team/journal/New-Label-Requirement-for-AI-Artwork-966421077. Retrieved on Jan 1, 2024.

[29] DeviantArt. 2024. DeviantArt Platform Metric. https://deviantartads.com/. Retrieved on Mar 18, 2024.

[30] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *CoRR* abs/1810.04805 (2018). arXiv:1810.04805 http://arxiv.org/abs/1810.04805

[31] Andrés Domínguez Hernández, Shyam Krishna, Antonella Maia Perini, Michael Katell, SJ Bennett, Ann Borda, Youmna Hashem, Semeli Hadjiloizou, Sabeehah Mahomed, Smera Jayadeva, et al. 2024. Mapping the individual, social and biospheric impacts of Foundation Models. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*. 776–796.

[32] Shachar Don-Yehiya, Leshem Choshen, and Omri Abend. 2023. Human Learning by Model Feedback: The Dynamics of Iterative Prompting with Midjourney. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, Singapore, 4146–4161.

[33] Anil R Doshi and Oliver Hauser. 2023. Generative artificial intelligence enhances creativity. *Available at SSRN* (2023).

[34] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. 2020. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929* (2020).

[35] Steven P. Dow, Kate Heddleston, and Scott R. Klemmer. 2009. The efficacy of prototyping under time constraints. In *Proceedings of the Seventh ACM Conference on Creativity and Cognition* (Berkeley, California, USA) *(C&C '09)*. Association for Computing Machinery, New York, NY, USA, 165–174. https://doi.org/10.1145/1640233.1640260

[36] Xiao Fang, Shangkun Che, Minjia Mao, Hongzhe Zhang, Ming Zhao, and Xiaohang Zhao. 2023. Bias of AI-generated content: an examination of news produced by large language models. *Scientific Reports* 14 (2023).

[37] Yunhe Feng, Pradhyumna Poralla, Swagatika Dash, Kaicheng Li, Vrushabh Desai, and Meikang Qiu. 2023. The Impact of ChatGPT on Streaming Media: A Crowdsourced and Data-Driven Analysis using Twitter and Reddit. In *2023 IEEE 9th Intl Conference on Big Data Security on Cloud (BigDataSecurity), IEEE Intl Conference on High Performance and Smart Computing, (HPSC) and IEEE Intl Conference on Intelligent Data and Security (IDS)*. 222–227. https://doi.org/10.1109/BigDataSecurity-HPSC-IDS58521.2023.00046

[38] Casey Fiesler and Amy S Bruckman. 2019. Creativity, copyright, and close-knit communities: a case study of social norm formation and enforcement. *Proceedings of the ACM on Human-Computer Interaction* 3, GROUP (2019), 1–24.

[39] Casey Fiesler and Brianna Dym. 2020. Moving across lands: Online platform migration in fandom communities. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW1 (2020), 1–25.

[40] Casey Fiesler, Jessica L Feuston, and Amy S Bruckman. 2015. Understanding copyright law in online creative communities. In *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing*. 116–129.

[41] Eureka Foong, Steven P Dow, Brian P Bailey, and Elizabeth M Gerber. 2017. Online feedback exchange: A framework for understanding the socio-psychological factors. In *Proceedings of the 2017 CHI Conference on Human Factors in*

Computing Systems. 4454–4467.

[42] Paula Fortuna and Sérgio Nunes. 2018. A Survey on Automatic Detection of Hate Speech in Text. *ACM Comput. Surv.* 51, 4, Article 85 (jul 2018), 30 pages. https://doi.org/10.1145/3232676

[43] Giancarlo F. Frosio. 2023. Should We Ban Generative AI, Incentivise it or Make it a Medium for Inclusive Creativity? *SSRN Electronic Journal* (2023).

[44] Patryk Galuszka. 2024. The influence of generative AI on popular music: Fan productions and the reimagination of iconic voices. *Media, Culture & Society* (2024), 01634437241282382.

[45] Samuel Gehman, Suchin Gururangan, Maarten Sap, Yejin Choi, and Noah A. Smith. 2020. RealToxicityPrompts: Evaluating Neural Toxic Degeneration in Language Models. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, Trevor Cohn, Yulan He, and Yang Liu (Eds.). Association for Computational Linguistics, Online, 3356–3369. https://doi.org/10.18653/v1/2020.findings-emnlp.301

[46] Wendy Grossman. 1997. *Net. Wars.* NYU Press, New York, NY, USA.

[47] Qingyu Guo, Chuhan Shi, Zhuohao Yin, Chengzhong Liu, and Xiaojuan Ma. 2023. Exploring the Effects of Event-induced Sudden Influx of Newcomers to Online Pop Music Fandom Communities: Content, Interaction, and Engagement. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW2 (2023), 1–24.

[48] Qingyu Guo, Chao Zhang, Hanfang Lyu, Zhenhui Peng, and Xiaojuan Ma. 2023. What Makes Creators Engage with Online Critiques? Understanding the Role of Artifacts' Creation Stage, Characteristics of Community Comments, and their Interactions. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–17.

[49] Kilem Li Gwet. 2008. Computing inter-rater reliability and its variance in the presence of high agreement. *Brit. J. Math. Statist. Psych.* 61, 1 (2008), 29–48.

[50] Philipp Hacker, Andreas Engel, and Marco Mauer. 2023. Regulating ChatGPT and other Large Generative AI Models. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (Chicago, IL, USA) *(FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 1112–1123. https://doi.org/10.1145/3593013.3594067

[51] Thilo Hagendorff. 2024. Mapping the Ethics of Generative AI: A Comprehensive Scoping Review. *ArXiv* abs/2402.08323 (2024).

[52] Hans WA Hanley and Zakir Durumeric. 2024. Machine-made media: Monitoring the mobilization of machine-generated articles on misinformation and mainstream news websites. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 18. 542–556.

[53] Ehsan-Ul Haq, Tristan Braud, Lik-Hang Lee, Anish K. Vallapuram, Yue Yu, Gareth Tyson, and Pan Hui. 2022. Short, Colorful, and Irreverent! A Comparative Analysis of New Users on WallstreetBets During the Gamestop Short-Squeeze. In *Companion Proceedings of the Web Conference 2022* (Virtual Event, Lyon, France) *(WWW '22)*. Association for Computing Machinery, New York, NY, USA, 52–61.

[54] Mohammed Mehedi Hasan, Mahady Hasan, and Jannat Un Nayeem. 2023. An Exploratory Analysis of Community-Based Question-Answering Platforms and Gpt-3-Driven Generative Ai: Is it the End of Online Community-Based Learning? *Available at SSRN 4450320* (2023).

[55] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 770–778.

[56] C Blaine Horton Jr, Michael W White, and Sheena S Iyengar. 2023. Bias against AI art can enhance perceptions of human creativity. *Scientific reports* 13, 1 (2023), 19001.

[57] Hongxian Huang, Runshan Fu, and Anindya Ghose. 2023. Generative AI and Content-Creator Economy: Evidence from Online Content Creation Platforms. *Available at SSRN 4670714* (2023).

[58] Shilan Huang and Dion Hoe-Lian Goh. 2024. Public Perceptions of GAI: A YouTube Analysis of Sora. *Proceedings of the Association for Information Science and Technology* 61, 1 (2024), 940–942.

[59] Will Hudgins, Michael Lynch, Ash Schmal, Harsh Sikka, Michael Swenson, and David A Joyner. 2020. Informal Learning Communities: The Other Massive Open Online'C'. In *Proceedings of the Seventh ACM Conference on Learning@ Scale*. 91–101.

[60] Clayton Hutto and Eric Gilbert. 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. *Proceedings of the International AAAI Conference on Web and Social Media* 8, 1 (2014), 216–225.

[61] Rob Hyndman, George Athanasopoulos, Christoph Bergmeir, Gabriel Caceres, Leanne Chhay, Mitchell O'Hara-Wild, Fotios Petropoulos, Slava Razbash, Earo Wang, and Farah Yasmeen. 2024. *forecast: Forecasting functions for time series and linear models*. https://pkg.robjhyndman.com/forecast/ R package version 8.23.0.

[62] Shagun Jhaver, Christian Boylston, Diyi Yang, and Amy Bruckman. 2021. Evaluating the Effectiveness of Deplatforming as a Moderation Strategy on Twitter. *Proceedings of the ACM on Human-Computer Interaction* 5 (2021), 1 – 30.

[63] Harry H Jiang, Lauren Brown, Jessica Cheng, Mehtab Khan, Abhishek Gupta, Deja Workman, Alex Hanna, Johnathan Flowers, and Timnit Gebru. 2023. AI Art and its Impact on Artists. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society*. 363–374.

[64] Samia Kabir, David N Udo-Imeh, Bonan Kou, and Tianyi Zhang. 2024. Is stack overflow obsolete? an empirical study of the characteristics of chatgpt answers to stack overflow questions. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–17.

[65] Eun Jeong Kang, Haesoo Kim, Hyunwoo Kim, and Juho Kim. 2022. When AI Meets the K-Pop culture: A case study of fans' perception of AI Private Call. In *AI Cultures. A NeurIPS 2022 Workshop (20.01. 2023)*.

[66] Yanfei Kang, Rob J. Hyndman, and Kate Smith-Miles. 2017. Visualising forecasting algorithm performance using time series instance spaces. *International Journal of Forecasting* 33, 2 (2017), 345–358. https://doi.org/10.1016/j.ijforecast.2016.09.004

[67] Reishiro Kawakami and Sukrit Venkatagiri. 2024. The Impact of Generative AI on Artists. In *Proceedings of the 16th Conference on Creativity & Cognition* (Chicago, IL, USA) *(C&C '24)*. Association for Computing Machinery, New York, NY, USA, 79–82. https://doi.org/10.1145/3635636.3664263

[68] Shahedul Huq Khandkar. 2009. Open coding. *University of Calgary* 23, 2009 (2009).

[69] Joy Kim, Maneesh Agrawala, and Michael S Bernstein. 2017. Mosaic: designing online creative communities for sharing works-in-progress. In *Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing*. 246–258.

[70] Taewook Kim, Hyomin Han, Eytan Adar, Matthew Kay, and John Joon Young Chung. 2024. Authors' Values and Attitudes Towards AI-bridged Scalable Personalization of Creative Language Arts. *arXiv preprint arXiv:2403.00439* (2024).

[71] Michael Koch, Kai von Luck, Jan Schwarzer, and Susanne Draheim. 2018. The novelty effect in large display deployments–Experiences and lessons-learned for evaluating prototypes. In *Proceedings of 16th European conference on computer-supported cooperative work-exploratory papers*. European Society for Socially Embedded Technologies (EUSSET).

[72] Evangelos Kontopantelis, Tim Doran, David A. Springate, Iain Buchan, and David Reeves. 2015. Regression based quasi-experimental approach when randomisation is not an option: interrupted time series analysis. *The BMJ* 350 (2015).

[73] Yubo Kou and Colin M Gray. 2017. Supporting distributed critique through interpretation and sense-making in an online creative community. *Proceedings of the ACM on Human-Computer Interaction* 1, CSCW (2017), 1–18.

[74] Sarah Kreps, R. Miles McCain, and Miles Brundage. 2022. All the News That's Fit to Fabricate: AI-Generated Text as a Tool of Media Misinformation. *Journal of Experimental Political Science* 9, 1 (2022), 104–117. https://doi.org/10.1017/XPS.2020.37

[75] Eva Cheuk-Yin Li and Ka-Wei Pang. 2024. Fandom meets artificial intelligence: Rethinking participatory culture as human–community–machine interactions. *European Journal of Cultural Studies* (2024), 13675494241236146.

[76] Siyu Li, Jin Yang, and Kui Zhao. 2023. Are you in a masquerade? exploring the behavior and impact of large language model driven social bots in online social networks. *arXiv preprint arXiv:2307.10337* (2023).

[77] Tao Li, Chin-Yi Cheng, Amber Xie, Gang Li, and Yang Li. 2024. Revision Matters: Generative Design Guided by Revision Edits. *arXiv preprint arXiv:2406.18559* (2024).

[78] Zhiyuan Lin, Niloufar Salehi, Bowen Yao, Yiqi Chen, and Michael Bernstein. 2017. Better when it was smaller? community content and behavior after massive growth. *Proceedings of the International AAAI Conference on Web and Social Media* 11, 1 (2017), 132–141.

[79] Vivian Liu, Han Qiao, and Lydia Chilton. 2022. Opal: Multimodal Image Generation for News Illustration. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology* (Bend, OR, USA) *(UIST '22)*. Association for Computing Machinery, New York, NY, USA, Article 73, 17 pages. https://doi.org/10.1145/3526113.3545621

[80] Travis Lloyd, Joseph Reagle, and Mor Naaman. 2023. " There Has To Be a Lot That We're Missing": Moderating AI-Generated Content on Reddit. *arXiv preprint arXiv:2311.12702* (2023).

[81] Ryan Louie, Andy Coenen, Cheng Zhi Huang, Michael Terry, and Carrie J. Cai. 2020. Novice-AI Music Co-Creation via AI-Steering Tools for Deep Generative Models. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376739

[82] Yao Lyu, He Zhang, Shuo Niu, and Jie Cai. 2024. A Preliminary Exploration of YouTubers' Use of Generative-AI in Content Creation. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. 1–7.

[83] Jennifer Marlow and Laura Dabbish. 2014. From rookie to all-star: professional development in a graphic design social networking site. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work and Social Computing*. ACM, New York, NY, USA, 922–933.

[84] Hana Matatov, Marianne Aubin Le Quéré, Ofra Amir, and Mor Naaman. 2024. Examining the Prevalence and Dynamics of AI-Generated Media in Art Subreddits. *arXiv preprint arXiv:2410.07302* (2024).

[85] Uwe Messer. 2024. Co-creating art with generative artificial intelligence: Implications for artworks and artists. *Computers in Human Behavior: Artificial Humans* (2024).

[86] Reza Hadi Mogavi, Derrick Wang, Joseph Tu, Hilda Hadan, Sabrina A Sgandurra, Pan Hui, and Lennart E Nacke. 2024. Sora OpenAI's Prelude: Social Media Perspectives on Sora OpenAI and the Future of AI Video Generation. *arXiv preprint arXiv:2403.14665* (2024).
[87] Dat Quoc Nguyen, Thanh Vu, and Anh Tuan Nguyen. 2020. BERTweet: A pre-trained language model for English Tweets. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*. 9–14.
[88] Sachita Nishal and Nicholas Diakopoulos. 2024. Envisioning the applications and implications of generative AI for news media. *arXiv preprint arXiv:2402.18835* (2024).
[89] Shakked Noy and Whitney Zhang. 2023. Experimental evidence on the productivity effects of generative artificial intelligence. *Science* 381, 6654 (2023), 187–192. https://doi.org/10.1126/science.adh2586
[90] Richard L Oliver. 1980. A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of marketing research* 17, 4 (1980), 460–469.
[91] Jonas Oppenlaender, Rhema Linder, and Johanna Silvennoinen. 2023. Prompting ai art: An investigation into the creative skill of prompt engineering. *arXiv preprint arXiv:2303.13534* (2023).
[92] Maxime Oquab, Timothée Darcet, Théo Moutakanni, Huy Vo, Marc Szafraniec, Vasil Khalidov, Pierre Fernandez, Daniel Haziza, Francisco Massa, Alaaeldin El-Nouby, et al. 2023. Dinov2: Learning robust visual features without supervision. *arXiv preprint arXiv:2304.07193* (2023).
[93] Ruchi Panchanadikar and Guo Freeman. 2024. " I'm a Solo Developer but AI is My New Ill-Informed Co-Worker": Envisioning and Designing Generative AI to Support Indie Game Development. *Proceedings of the ACM on Human-Computer Interaction* 8, CHI PLAY (2024), 1–26.
[94] Ruchi Panchanadikar, Guo Freeman, Lingyuan Li, Kelsea Schulenberg, and Yang Hu. 2024. " A New Golden Era" or" Slap Comps": How Non-Profit Driven Indie Game Developers Perceive the Emerging Role of Generative AI in Game Development. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. 1–7.
[95] Joon Sung Park, Joseph O'Brien, Carrie Jun Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein. 2023. Generative Agents: Interactive Simulacra of Human Behavior. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology* (San Francisco, CA, USA) *(UIST '23)*. Association for Computing Machinery, New York, NY, USA, Article 2, 22 pages. https://doi.org/10.1145/3586183.3606763
[96] Anna Maria Piskopani, Alan Chamberlain, and Carolyn Ten Holter. 2023. Responsible AI and the Arts: The Ethical and Legal Implications of AI in the Arts and Creative Industries. In *Proceedings of the First International Symposium on Trustworthy Autonomous Systems* (Edinburgh, United Kingdom) *(TAS '23)*. Association for Computing Machinery, New York, NY, USA, Article 48, 5 pages. https://doi.org/10.1145/3597512.3597528
[97] Robin L Plackett. 1983. Karl Pearson and the chi-squared test. *International statistical review/revue internationale de statistique* (1983), 59–72.
[98] Martin Ragot, Nicolas Martin, and Salomé Cojean. 2020. AI-generated vs. Human Artworks. A Perception Bias Towards Artificial Intelligence?. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI EA '20)*. Association for Computing Machinery, New York, NY, USA, 1–10.
[99] Jiawei Ren, Cunjun Yu, Xiao Ma, Haiyu Zhao, Shuai Yi, et al. 2020. Balanced meta-softmax for long-tailed visual recognition. *Advances in neural information processing systems* 33 (2020), 4175–4186.
[100] Everett M Rogers, Arvind Singhal, and Margaret M Quinlan. 2014. Diffusion of innovations. In *An integrated approach to communication theory and research*. Routledge, 432–448.
[101] Koustuv Saha, Pranshu Gupta, Gloria Mark, Emre Kıcıman, and Munmun De Choudhury. 2024. Observer Effect in Social Media Use. *Proceedings of the CHI Conference on Human Factors in Computing Systems* (2024).
[102] Téo Sanchez. 2023. Examining the Text-to-Image Community of Practice: Why and How do People Prompt Generative AIs?. In *Proceedings of the 15th Conference on Creativity and Cognition*. 43–61.
[103] Christina Sterbenz. 2022. DeviantArt's Decision to Label AI Images Creates a Vicious Debate Among Artists and Users. https://www.artnews.com/art-news/news/deviantart-artficial-intelligence-ai-images-midjourney-stabilityai-art-1234674400/. Retrieved on Mar 1, 2024.
[104] Yuan Sun, Eunchae Jang, Fenglong Ma, and Ting Wang. 2024. Generative AI in the Wild: Prospects, Challenges, and Strategies. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–16.
[105] Amaury Trujillo and Stefano Cresci. 2022. Make Reddit Great Again: Assessing Community Effects of Moderation Interventions on r/The_Donald. *Proceedings of the ACM on Human-Computer Interaction* 6 (2022), 1 – 28.
[106] Charles Truong, Laurent Oudre, and Nicolas Vayatis. 2020. Selective review of offline change point detection methods. *Signal Processing* 167 (2020), 107299.
[107] Tommaso Turchi, Silvio Carta, Luciano Ambrosini, and Alessio Malizia. 2023. Human-AI Co-creation: Evaluating the Impact of Large-Scale Text-to-Image Generative Models on the Creative Process. In *End-User Development*, Lucio Davide Spano, Albrecht Schmidt, Carmen Santoro, and Simone Stumpf (Eds.). Springer Nature Switzerland, Cham, 35–51.

[108] Eddie Ungless, Bjorn Ross, and Anne Lauscher. 2023. Stereotypes and Smut: The (Mis)representation of Non-cisgender Identities by Text-to-Image Models. In *Findings of the Association for Computational Linguistics: ACL 2023*, Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (Eds.). Association for Computational Linguistics, Toronto, Canada, 7919–7942. https://doi.org/10.18653/v1/2023.findings-acl.502

[109] Cristian Vaccari and Andrew Chadwick. 2020. Deepfakes and Disinformation: Exploring the Impact of Synthetic Political Video on Deception, Uncertainty, and Trust in News. *Social Media + Society* 6 (2020).

[110] Pramukh Nanjundaswamy Vasist and Satish Krishnan. 2022. Deepfakes: An Integrative Review of the Literature and an Agenda for Future Research. *Commun. Assoc. Inf. Syst.* 51 (2022), 14.

[111] Liuping Wang, Dakuo Wang, Feng Tian, Zhenhui Peng, Xiangmin Fan, Zhan Zhang, Mo Yu, Xiaojuan Ma, and Hongan Wang. 2021. Cass: Towards building a social-support chatbot for online health community. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–31.

[112] Liang Wang, Nan Yang, Xiaolong Huang, Linjun Yang, Rangan Majumder, and Furu Wei. 2024. Multilingual E5 Text Embeddings: A Technical Report. *arXiv preprint arXiv:2402.05672* (2024).

[113] Sitong Wang, Samia Menon, Tao Long, Keren Henderson, Dingzeyu Li, Kevin Crowston, Mark Hansen, Jeffrey V Nickerson, and Lydia B Chilton. 2024. ReelFramer: Human-AI co-creation for news-to-video translation. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–20.

[114] Sitong Wang, Savvas Petridis, Taeahn Kwon, Xiaojuan Ma, and Lydia B Chilton. 2023. PopBlends: Strategies for conceptual blending with large language models. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–19.

[115] Zhijie Wang, Yuheng Huang, Da Song, Lei Ma, and Tianyi Zhang. 2024. PromptCharm: Text-to-Image Generation through Multi-modal Prompting and Refinement. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 185, 21 pages. https://doi.org/10.1145/3613904.3642803

[116] Jason Wei and Kai Zou. 2019. Eda: Easy data augmentation techniques for boosting performance on text classification tasks. *arXiv preprint arXiv:1901.11196* (2019).

[117] Yiluo Wei and Gareth Tyson. 2024. Understanding the Impact of AI Generated Content on Social Media: The Pixiv Case. *ArXiv* abs/2402.18463 (2024).

[118] Yiluo Wei, Yiming Zhu, Pan Hui, and Gareth Tyson. 2024. Exploring the Use of Abusive Generative AI Models on Civitai. In *Proceedings of the 32nd ACM International Conference on Multimedia*. 6949–6958.

[119] Laura Weidinger, Jonathan Uesato, Maribeth Rauh, Conor Griffin, Po-Sen Huang, John Mellor, Amelia Glaese, Myra Cheng, Borja Balle, Atoosa Kasirzadeh, Courtney Biles, Sasha Brown, Zac Kenton, Will Hawkins, Tom Stepleton, Abeba Birhane, Lisa Anne Hendricks, Laura Rimell, William Isaac, Julia Haas, Sean Legassick, Geoffrey Irving, and Iason Gabriel. 2022. Taxonomy of Risks posed by Language Models. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (Seoul, Republic of Korea) *(FAccT '22)*. Association for Computing Machinery, New York, NY, USA, 214–229. https://doi.org/10.1145/3531146.3533088

[120] Robert Wolfe, Yiwei Yang, Bill Howe, and Aylin Caliskan. 2023. Contrastive Language-Vision AI Models Pretrained on Web-Scraped Multimodal Data Exhibit Sexual Objectification Bias *(FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 1174–1185. https://doi.org/10.1145/3593013.3594072

[121] Jiayang Wu, Wensheng Gan, Zefeng Chen, Shicheng Wan, and Hong Lin. 2023. Ai-generated content (aigc): A survey. *arXiv preprint arXiv:2304.06632* (2023).

[122] Y. Wayne Wu and Brian P. Bailey. 2017. Bitter Sweet or Sweet Bitter? How Valence Order and Source Identity Influence Feedback Acceptance. In *Proceedings of the SIGCHI Conference on Creativity and Cognition*. ACM, New York, NY, USA, 137–147.

[123] Yutong Xie, Zhaoying Pan, Jinge Ma, Luo Jie, and Qiaozhu Mei. 2023. A prompt log analysis of text-to-image generation systems. In *Proceedings of the ACM Web Conference 2023*. 3892–3902.

[124] Anbang Xu and Brian Bailey. 2012. What do you think? A case study of benefit, expectation, and interaction in a large online critique community. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work and Social Computing*. ACM, New York, NY, USA, 295–304.

[125] Anbang Xu, Shih-Wen Huang, and Brian Bailey. 2014. Voyant: generating structured feedback on visual designs using a crowd of non-experts. In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing* (Baltimore, Maryland, USA) *(CSCW '14)*. Association for Computing Machinery, New York, NY, USA, 1433–1444. https://doi.org/10.1145/2531602.2531604

[126] Pinar Yanardag, Manuel Cebrian, and Iyad Rahwan. 2021. Shelley: A Crowd-sourced Collaborative Horror Writer. In *Proceedings of the 13th Conference on Creativity and Cognition* (Virtual Event, Italy) *(C&C '21)*. Association for Computing Machinery, New York, NY, USA, Article 11, 8 pages. https://doi.org/10.1145/3450741.3465251

[127] Kai-Cheng Yang and Filippo Menczer. 2023. Anatomy of an AI-powered malicious social botnet. *ArXiv* abs/2307.16336 (2023).

[128] Xiaoke Zhang, Mi Zhou, and Gene Moo Lee. 2024. How Does AI-Generated Voice Affect Online Video Creation? Evidence from TikTok. (2024). Available at SSRN: http://dx.doi.org/10.2139/ssrn.4676705.

[129] Eric Zhou and Dokyun Lee. 2024. Generative ai, human creativity, and art. *Eric Zhou, Dokyun Lee, Generative artificial intelligence, human creativity, and art, PNAS Nexus* 3, 3 (2024).

[130] Kyrie Zhixuan Zhou, Abhinav Choudhry, Ece Gumusel, and Madelyn Rose Sanfilippo. 2024. " Sora is Incredible and Scary": Emerging Governance Challenges of Text-to-Video Generative AI Models. *arXiv preprint arXiv:2406.11859* (2024).

[131] Yuqi Zhou, Sunhao Dai, Liang Pang, Gang Wang, Zhenhua Dong, Jun Xu, and Ji-Rong Wen. 2024. Source Echo Chamber: Exploring the Escalation of Source Bias in User, Data, and Recommender System Feedback Loop. *arXiv preprint arXiv:2405.17998* (2024).

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