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

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ABSTRACT

The rise of AI-generated content (AIGC) is transforming online creative communities (OCCs) and posing challenges to their regulation. Artwork description may reveal creators' practice and motivation in creating and sharing artwork. Understanding the influence of AIGC on creators' descriptions of shared artwork could be helpful for community regulation. In this work, we collect 235K posts from DeviantArt, a large creative community that allows uploading AIGC. We confirm the prevalence of AIGC in the community. Through an open coding on 800 randomly sampled posts, we identify five themes in artwork descriptions. We quantitatively examine how these themes are affected by the prevalence of AIGC via statistical analysis. Results indicate a shift towards commercial opportunities and a reduced focus on copyright since the prevalence of AIGC. Descriptions for AI-generated artworks are more likely to direct members to other creations than those for human-created artworks. Finally, we discuss insights for OCCs.

CCS CONCEPTS

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

KEYWORDS

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). AIGC is progressively replacing user-generated content (UGC) in daily lifes [41] and consequently, reshaping the norms within online communities. For example, online creative communities like DeviantArt [11] 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 for skill learning, entertainment, and professional development by showcasing creation and interacting with remote peers [16, 27]. Generative AI tools, such as DALL-E, Stable Diffusion, and Midjourney, on the one hand, may enhance these benefits as they increase the productivity of creators and encourage broad participation by lowering barriers to artwork creation [28, 43]. On the other hand, they may threaten the regulation of online creativity communities by potentially introducing low-quality creation, triggering conflicts of attitude toward AIGC, and arousing copyright issues around AIGC [1, 33].

While previous studies have investigated the potential impact of generative AI on the creation output and community regulation, less is known about how generative AI might influence creators' descriptions of their artwork. Creators' artwork description could not only provide information about artwork creation but also convey creators' motivation for joining the community and sharing the artwork [7, 8, 20]. In this work, we aim to understand the themes presented in the creators' descriptions attached to the shared artworks and how these themes were affected by the increasing prevalence of AIGC within the community. The resulting understanding could provide valuable insights into the evolving practices of creation and community dynamics in response to the technology-driven surges. Such knowledge is also important for the effective regulation of online creative communities to foster creativity and accommodate members' needs [5, 17].

To this end, we utilize data from the DeviantArt platform to address the research questions. Deviantart is one of the largest online communities dedicated to artwork sharing and allows the uploading of AIGC. Our data involved randomly sampled 235K posts from August 2020 to November 2023, covering the period before the release of generative AI techniques to the prevalence of AIGC. We trained a visual-based AI art classifier to identify the AI-generated artwork in the sampled data. Using a time series algorithm, we identified the prevalence period of AIGC in the community, which began in September 2022. We then randomly sampled 800 posts in the collected dataset and conducted open coding to identify how creators described their shared artworks. Through open coding, we revealed five themes in the artwork description – 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 then analyzed the changes in artworks descriptions from the period before AIGC prevalence to the AIGC prevalence period, as well as how the usage of generative AI techniques influenced the artwork description during the AIGC prevalence period. Results showed that since AIGC started to be prevalent in the community, the focus of community posting shifted toward commercial opportunities accompanied by a decreased awareness of IP issues. Compared to the descriptions for human-created artworks, descriptions for AI-generated artworks exhibited a lower emphasis on the current artifact while having a higher chance of guiding viewers to other creations. Our studies reveal the impact of generative AI on the norms of the creative community and provide insights for community moderation under the surge of AIGC.

2 BACKGROUND

We highlight relevant literature in two areas to better situate the study.

Generative AI and Content Creator. Recent studies have revealed the motivation and barriers of creators in adopting generative AI [1, 37], and examined the usage pattern in human-ai co-creation process [14, 31, 34, 42]. Several works also identified the potential impact of generative AI on creators, such as copyright and ethical issues [28], and quality and productivity of the creative output [26, 43]. In short, previous studies provide insights into the impact of generative AI on the creation process and output. Different from previous works, we focus on the sharing practice of creators by examining data in an online community.

Online Community Evolution. Previous studies have suggested multiple triggers could lead to changes in community content and norms, such as platform setting changes [18], platform promotions [4, 32], and real-world events [19, 22]. The rapid development of generative AI technologies is reshaping the paradigm of content production and bringing a new dimension to investigating community dynamics. In recent years, studies examined the change in user activity on community question-answering platforms (e.g., Stack Overflow) as large language models are becoming popular [3, 23]. Chen et al. [6] examined the evolvement of the content in AI-generated artworks on Twitter. However, they often ignored how the norms in sharing evolve as generative AI becomes popular. This work complements previous studies by examining the current practice of artwork sharing and investigating how generative AI may affect sharing norms. Such understanding is important for the moderation of the online creative community in the era of AIGC.

3 METHOD

3.1 Research Site and Data Collection

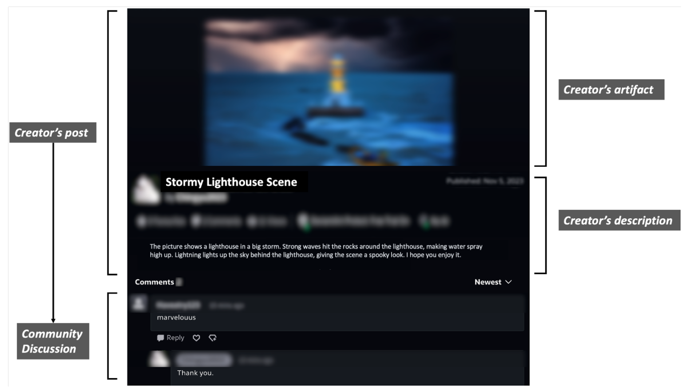


Figure 1: Example artwork published on the DeviantArt platform. We decrease the resolution and obscure sensitive information for copyright and privacy concerns. We slightly paraphrased the content in the post so that the post could not be searched.

DeviantArt is one of the largest artist communities. In 2024, DeviantArt reported over 700 million page views per month [13]. Figure 1 is an example of artwork published on the platform. Artists can share their created artifact along with an introduction (such as the artifact title and a description). They can also 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 a platform-generated artwork ID. After examining 1000 randomly sampled artworks published in November 2023, we found a Spearman correlation of over 0.97 between the ID and the artwork published time. This indicates that most artwork IDs are in ascending order according to their publication time, with newer projects having larger IDs. To capture the recent trend of community content, we scraped artifacts by randomly sampling IDs starting from a project 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). For example, we excluded "journals" where creators often share personal experiences but may not include artwork. 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. The scraped information includes the URL of the artifact and the metadata associated with the posts, such as the title, description, and creator username.

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 [6, 43], 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 resulted in a total of 22,747 human-created projects. Additionally, the DeviantArt platform requires users to indicate whether they utilized AI techniques in their creations [12]. 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 [24], and Vision-Transformer-based models such as ViT [15], BEiT [2], and DINOv2 [35]. We compared their performance on the validation set. The BEiT model, which was pre-trained on ImageNet-22k dataset [10], 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. With the BEiT model, we predict 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 [1]. Another explanation is that creators might prefer their artworks to be evaluated based on artistic merit rather than on how they were created [25]. Future works could delve deeper into the reasons behind this phenomenon through qualitative research.

3.3 Creator Sharing Practice Identification

We utilized an open coding approach [29] to identify creators' practices in sharing 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 the three researchers 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 from 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 [21]. After the iteration process to refine the codebook, they finally discussed inter-code connections and clustered related codes, yielding high-level themes. 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 analysis.

4 RESULT

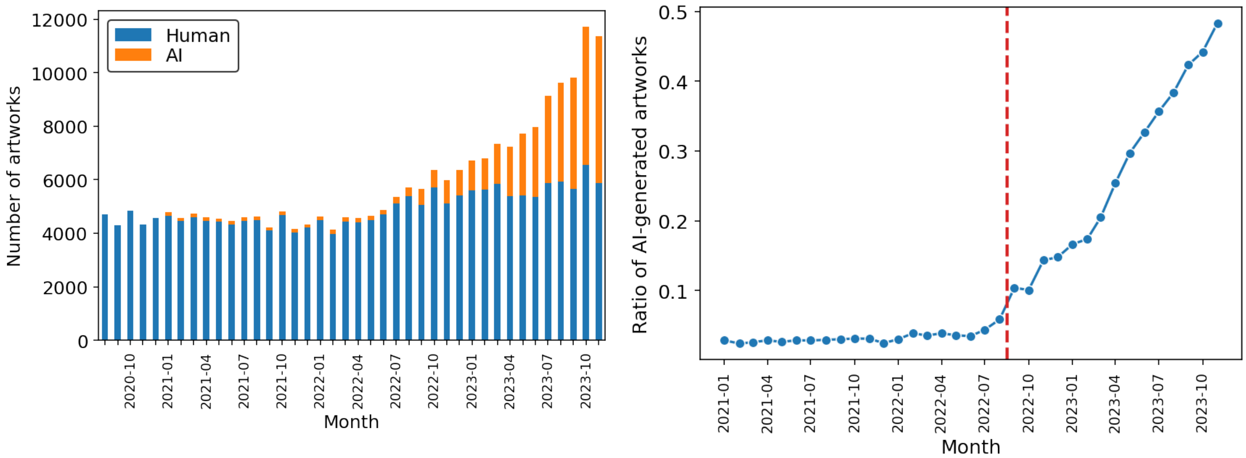
4.1 Trend of AI-Generated Artworks in Community

Figure 2a 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 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 shifted greatly due to generative AI techniques.

To capture the transformation UGC and AIGC within the community, we computed the proportion of AI-generated artworks relative to the total monthly uploaded artworks (as shown in Figure 2b). We applied a widely adopted change point detection algorithm [39] to identify the inception of the AI artwork's prevalence within the community. This algorithm leverages dynamic programming to identify optimal time series segments where subsequences can be most accurately modeled by different data distributions. We set the number of time series segments to two, aiming to identify a single significant change point in the ratio of AIGC. This approach was taken to distinguish the periods when AIGC was relatively rare and when it began to surge within the community. Following the common practice in [39], we assumed a Gaussian distribution for each segment, which can accommodate the monthly variability in the AIGC ratio as depicted in Figure 2b. The results of the algorithm suggest a significant change in the community's AI-generated artwork ratio after August 2022 (illustrated by the red vertical line in Figure 2b). This indicates a significant increase in the presence of AI-generated artwork within the community from that point onwards. Therefore, we define the period starting from September 2022 as the AIGC prevalence period, and the period preceding September 2022 as the pre-AIGC prevalence period.

4.2 Creators' Practice in Describing Artworks

Through our open coding, we uncovered multiple codes in creators' sharing and grouped them into the following perspectives related to creation. Table 1 lists detailed examples for each code.



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

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

Figure 2: The trend of AI-generated and human-created artworks in each month.

Table 1: 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.

Theme	Code	Definition	Example
Context of creation	Scenario	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	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	The tools and techniques adopted in the creation	– *Background added from photoshop*
	Collaborative information	Acknowledge or credit other members in the creation process	– *a friend and i wrote it*
Content of creation	Content overview	Brief introduction of the objectives in the artwork	– *Roses at the wall*
	Content narrative	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	Mention the copyright information of the creation	– *Character(s) presented do not belong to me*
	Usage instruction	Guidelines on using the artworks	– *Free of use with credits*
	Commercial	Information on purchasing the artwork	– *Status: OPEN (2/5 slots)Terms of service: Payment is upfront*
Community interaction around creation	Socialization	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	Suggestions for interacting for the artwork	– *What's your fave object out of all of these?*
	Promotion	provide external links to other artworks or portfolio	– *Follow my work here too: twitter.com/[USERNAME]*

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.

4.3 Impact of AIGC Prevalence on Artwork Description

We initiate our study by analyzing the evolution of artwork descriptions since the prevalence of AI-generated artworks within the community to illustrate the impact of AIGC on community practice. We divide the coded samples into two groups – 1) the control group comprises coded samples (N=408) pre-dating September 2022, the time before the AIGC surge within the community; 2) the experimental group consists of coded samples (N=392) from September 2022 onward. Each code is represented as a binary variable, either 0 or 1. Following the recommended practice in [30], we employ Fisher's exact test [40] when the frequency of codes (0 or 1) is less than five in any group. In cases where the frequency exceeds this threshold, the chi-squared test [36] is utilized. Table 2 lists the percentage of the sampled posts that contain the specific code. We also calculate 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. Artworks published during the AIGC prevalence period were less likely associated with scenarios ($OR = 0.52, p < 0.01$) and content narratives of the artwork ($OR = 0.75, p < 0.01$) than artworks shared before AIGC became popular in the community. Meanwhile, we notice a significant decrease ($OR = 0.55, p < 0.05$) in IP disclaimer for the shared artworks since the AIGC surge in the community than before the surge. This may indicate a decrease in creators' awareness of IP issues as the creative community transitions from UGC to AIGC. During the AIGC prevalence period, a significantly higher proportion ($OR = 2.72, p < 0.01$) of artworks containing commercial information were shared than those before the period. This may suggest a change in the creators' motivation to share the artworks. These results indicate an evolvement of the practice in describing the shared artworks in the community.

4.4 Impact of using Generative AI on Artwork Description during AIGC Prevalence Period

We then revealed how the adoption of generative AI techniques may affect the practice of describing the artworks during the AIGC prevalence period. We divide the coded posts during the AIGC prevalence period into two groups according to whether generative AI was adopted in the creation. We chose the coded posts for human-created artworks as the control group and those for AI-generated artworks as the experimental group, and conducted the same statistic analysis as in subsection 4.3. The proportion of the existence of codes was reported in Table 2. We observe a significantly lower proportion in the disclosure of the scenario ($OR = 0.20, p < 0.01$) and the inspiration attribution ($OR = 0.07, p < 0.001$) between AI-generated artworks and human-created artworks. Similarly, AI-generated artworks were associated with less description of content related to creation, no matter in the format of a general content overview ($OR = 0.89, p < 0.01$) or detailed content narrative ($OR = 0.39, p < 0.001$) than human-created artworks. Meanwhile, AI-generated artworks were less likely ($OR = 0.21, p < 0.05$) to announce IP disclaimer than human-created artworks. We also observed a significantly higher association level ($OR = 4.15, p < 0.001$) in disclosing utilized tools and techniques during creation for AI-generated artworks than human-created artworks. This may be due to the community rules in claiming the usage of AI for artworks. Similarly, AI-generated artworks were more likely to contain commercial information ($OR = 2.11, p < 0.05$) and promotion information ($OR = 2.24, p < 0.01$) than human-created artworks. These findings indicate that human creators of artworks may be driven by a desire to showcase their work, whereas creators of AI-generated artworks tend to leverage increased productivity for commercial purposes and greater exposure.

We further investigated whether the practice of describing human-created artworks varies before and during the prevalence of AIGC. No significant difference ($p > 0.05$) on all dimensions of the theme was observed between the descriptions for artworks before AIGC prevalence (N=408) and human-created artworks during AIGC prevalence (N=275). Similar results were observed when comparing the artwork description for human-created artworks shared before AIGC prevalence (N=401) and during AIGC prevalence (N=275). These indicate that the practice of sharing human-created artworks remained consistent despite the rise of generative AI.

5 DISCUSSION

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

First, we observed a shifting focus in describing the shared artworks from the pre-AIGC prevalence period to the AIGC prevalence period. While artworks before the prevalence period may have been driven by personal expression or sharing with the community, the prevalence of AIGC may have been shifting the focus toward commercial opportunities. One potential reason is that generative AI tools could accelerate the creation process and reduce manual effort than traditional approaches, and such scalability could open up new commercial opportunities for artists [9, 28]. Moreover, the automated and algorithmic nature of AIGC might result in a detachment from traditional creative processes involving personal experiences and storytelling [31]. As generative AI tools become more popular, members' motivation to share the post and needs may continue to evolve. Community moderators may need to reflect on the role of the creative community in the era of generative AI and accommodate the needs of community members.

Table 2: Percentage of posts that present the code in each group. In the table, ***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$.

Theme	Code	Before prevalence (N=408)	During prevalence (N=392)	Odds Ratio	During prevalence Human (N=275)	During prevalence AI (N=117)	Odds Ratio
Context of creation	Scenario	12.7%	6.6%	0.52 **	8.7%	1.7%	0.20 **
	Inspiration attribution	12.7%	8.9%	0.70	12.4%	0.9%	0.07 ***
Process of creation	Tools and techniques	4.7%	6.4%	1.36	3.3%	13.7%	4.15 ***
	Collaborative information	2.7%	1.0%	0.37	1.5%	0%	0
Content of creation	Content overview	89.7%	87.5%	0.98	90.5%	80.3%	0.89 **
	Content narrative	23.8%	17.9%	0.75 *	21.8%	8.5%	0.39 **
Dissemination of creation	IP disclaimer	11.0%	6.1%	0.55 *	8.0%	1.7%	0.21 *
	Usage instruction	6.1%	3.6%	0.59	2.9%	5.1%	1.76
	Commercial	3.2%	8.7%	2.72 **	6.5%	13.7%	2.11 *
Community interaction around creation	Socialization	16.2%	11.5%	0.71	11.3%	12.0%	1.06
	Interaction guidance	3.2%	5.1%	1.59	4.7%	5.98%	1.27
	Promotion	11.8%	11.0%	0.93	8.0%	17.9%	2.24 **

Second, the awareness of artworks' IP issues dropped from the pre-AIGC prevalence period to the AIGC prevalence period in the community. Notably, descriptions for AI-generated artworks presented fewer IP issues than human-created works during the AIGC prevalence period. One explanation might be that AI-generated artworks could blur the lines of traditional copyright concepts, leading to confusion and uncertainty regarding IP issues [28]. While IP-related discussion have always been a critical topic in the creative community [16], the result indicated a lack of guidelines specifically addressing IP issues related to AIGC. The creative community may also update guidelines in sharing artworks according to the trend of AIGC. It would also be interesting to explore how the change in community practice of IP issues may further affect the community norms and IP awareness of community members.

Third, during the AIGC prevalence period, descriptions for AI-generated artworks exhibited a decreased emphasis on the current artifact while an increased trend to guiding viewers to other creations compared to that for human-created artworks. A possible reason might be generative AI tools increase the productivity of creators [43], who may not carry the same level of personal attachment or significance as those without using the tool in creation, and be more inclined to guide community members toward other creations. Future studies can further explore the reasons behind variation in sharing practice in the prevalence of AIGC through a qualitative study and how such behaviors may affect the development of the online creative community.

This research opens multiple directions. First, it would be valuable to explore shifts in community members' reception of community content and the evolvement of community interactions as AIGC becomes more prevalent in the community. Second, future research could explore the impact of AIGC in various creative communities, such as for writing, music, and video sharing. To extend our research and examine the generalizability of results from our study, future works should consider the trend of generative AI tools for each type of artifact and the differences in norms and practices within these communities.

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 intrinsic distribution on the platform. Second, while the open coding process could ensure the reliability of data for analysis, it limits the sample size for analysis. In the future, we will train classifiers to identify the themes in artworks' description and examine the trend in the entire dataset. Third, there remain other factors that may influence the artwork descriptions. For example, the 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 [38]. Therefore, the changes in artwork descriptions may not be solely due to the AIGC's popularity but could have contributed to other factors. Future works should consider more comprehensive factors that may affect user behaviors and unpack such confounding biases when analyzing community dynamics.

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. Furthermore, we quantified the impact of AIGC prevalence on creators' descriptions in their shared artworks, shedding light on the evolving nature of the creative community in the era of AIGC.

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