SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Artificial Intelligence and Education 2025, 1(1), 1624.
https://doi.org/10.62617/aie1624

Article

Creators' perceptions and attitudes toward using generative artificial intelligence: Exploring posts and comments related to AIGC design learning on a Chinese social media platform with a mixed-method approach

Wenyi Li

The School of Computer Science, Peking University, Beijing 100871, China; liwenyi@pku.edu.cn

CITATION

Li W. Creators' perceptions and attitudes toward using generative artificial intelligence: Exploring posts and comments related to AIGC design learning on a Chinese social media platform with a mixed-method approach. Artificial Intelligence and Education. 2025; 1(1): 1624. https://doi.org/10.62617/aie1624

ARTICLE INFO

Received: 23 March 2025
Revised: 20 April 2025
Accepted: 25 April 2025
Available online: 26 June 2025

Abstract: Artificial intelligence generated content (AIGC) has been found to play a crucial role in the field of design, where its significance in various creative clusters has been increasingly recognized. However, the lack of in-depth understanding of creators' AIGC learning experiences and sentiments in the design area has become an obstacle to the further development of targeted educational programs and industry-relevant initiatives. It remains unclear what specific clusters of AIGC design learning creators are focusing on and what kinds of attitudes, positive or negative, they hold towards these different clusters within the field. To bridge these gaps, this study collected 9992 posts and comments related to AIGC design learning on a Chinese social media platform called Xiaohongshu. A mixed-method approach was applied by combining word cloud, sentiment analysis, co-word analysis, and social network analysis. Using word cloud and sentiment analysis, this research aimed to uncover the key perceptions and sentiment orientations creators focused on in their expression. Social network analysis and co-word matrix were used to identify central concepts, their connections and clusters of related terms. The result differentiates creators' perceptions into the following clusters: tools and technical foundations for AIGC design, application domains of AIGC design, cultural elements used in AIGC, semantic nuances in AIGC terminology, AIGC design methods, creativity and innovation in AIGC design, future-oriented perspectives in AIGC design for professional development, and AIGC design ethics. Moreover, it presents the tendencies and proportions of creators' attitudes in the above clusters in four main sentiment categories: positive, moderately positive, moderately negative, and negative. This study is expected to have implications in providing practical guidance for educators to optimize AIGC design teaching strategies, thereby better meeting learners' emotional needs and increasing their willingness to learn AIGC design knowledge, as well as helping the industry develop better AIGC-designed products.

Keywords: AIGC; design; creator; generative artificial intelligence; word cloud; sentiment analysis; social network analysis; social media

1. Introduction

In recent years, artificial intelligence generated content (AIGC) has emerged as a transformative force in various fields. Previous studies have also emphasized that the ability to use generative AI was a career-driven competency for pursuing a desired career path, which requires mastering relevant knowledge, technical skills, and ethics [1]. A growing body of research has revealed that AIGC technology plays significant roles in design for enhancing continuous innovation [2], developing creative thinking when designing architecture [3], and creating innovative design of furniture [4]. In addition, researchers have explored AIGC design from multiple dimensions involving designers' or creators' technological acceptance [5], self-efficacy in design education [6], computational thinking [7], and creativity in product design [8].

Despite the significance of AI-generated content for designing creations, researchers have pointed out the importance of ethics in architectural design focusing on professional ethical issues such as algorithmic bias, content sensitivity, and equitable application at a theoretical or technical level [9]. While these aspects are crucial, they leave out important elements such as users' sentiment towards AIGC design learning and the cultural nuances within this field. This study aims to fill these gaps by specifically focusing on creators' AIGC learning experiences, sentiments, and the cultural and semantic dimensions involved. By doing so, it offers a new perspective that has not been fully explored in previous research.

In addition, existing studies also show limitations of it, such as the lack of original design inspiration provision, flaws in design evaluation crucial for product success, and over-reliance on designers' experience for solution selection [10]. This indicates that researchers should not only focus on the impact enhanced by AIGC technology, but also deeply explore designers' various real experiences, perceptions, and sentiments regarding AIGC-based design. The role of exploring designers' sentiments when using AIGC for design has been noted by previous studies. For example, Li [11] found that certain dimensions (e.g., performance expectancy, effort expectancy, social influence, and facilitating conditions) have a positive relationship with the willingness to use AIGC tools, while some dimensions (e.g., perceived anxiety and perceived risk) also demonstrate a negative correlation with it. This indicates that when investigating designers' perceptions of AIGC design, both positive and negative clusters need to be taken into account. Otherwise, it is difficult to gain comprehensive insights into the real-world situation of AIGC design learning. To better understand the real-world learning challenges creators encounter when using generative AI tools, it is an effective approach to use the word cloud to identify commonly used words and employ sentiment analysis to analyze their positive or negative emotions on social platforms [12].

However, there is a scarcity of data-based research on the diverse perceptions of using AI in STEM education; therefore, there is an urgent need to use sentiment analysis to understand the changing views of public users expressed on social media [13]. To meet the above need, this study aims to use a mixed-method approach combining word cloud, sentiment analysis, co-word analysis, and social network analysis (SNA) to analyze the posts and comments related to AIGC design learning in social media. The primary objectives are to identify the most discussed topics in AIGC design learning, understand the distribution of users' sentiment, and provide industry stakeholders with a better understanding of user needs and preferences.

The research questions (RQ) of this study are as follows:

RQ1: What are the most prominent key concepts and themes that emerge from the word cloud analysis of creators' discussions regarding AIGC design learning, and how do these concepts reflect the current focus of AIGC design learning among creators?

RQ2: How do social network analysis and co-word analysis reveal the complex relationships among various keywords in creators' perceptions of AIGC design learning? Specifically, which are the central concepts, and how are they connected to form clusters of related terms within the context of AIGC design learning?

RQ3: What are the sentiment distributions (i.e., positive, moderately positive, moderately negative, negative) of creators towards AIGC design learning as determined by sentiment analysis, and how do these sentiment patterns vary across different aspects and clusters of AIGC design learning?

2. Materials and methods

2.1. Data collection

This study aims to analyze posts and comments about AIGC design learning on a public social media platform. Xiaohongshu is a well-known Chinese social media platform where people can share posts, images, and comments to showcase real-life lifestyles and public opinions [14]. Nowadays, Xiaohongshu has become the primary communication medium for young people in China, acting as a crucial information-sharing and social-interaction hub, which has been explored in a previous study by Tan [15] using the Technology Acceptance Model (TAM) to verify its user experience, information-sharing motivation, and perceived usefulness. Since AIGC learning represents a significant technological advancement, the TAM framework is highly relevant to understanding how users engage with AIGC-related content. Thus, Xiaohongshu, with its unique characteristics, provides an excellent platform for studying AIGC design learning.

When compared to Weibo, Xiaohongshu exhibits a distinct user-group behavior pattern. Its users are more focused on lifestyle sharing and interest-based communication. In the context of AIGC design learning, they show a greater inclination to share in-depth details of their learning processes, practical insights from using AIGC tools, and the outcomes of their design endeavors. This in-depth content sharing is invaluable, as it offers rich and detailed data for analyzing creators' perceptions and attitudes towards AIGC design learning. Conversely, Bilibili, despite its abundant resources in ACG culture and diverse creative content, poses challenges for our research. The content on Bilibili is predominantly in video format, and topic discussions are rather fragmented. This makes it difficult to extract and analyze text-based content specifically related to AIGC design learning. In contrast, Xiaohongshu's well-developed topic-tagging system is a significant asset. It enables precise filtering and collection of posts and comments directly relevant to AIGC design learning, which is essential for conducting in-depth and accurate analysis in this study.

Accordingly, Xiaohongshu was selected as the data source due to its rich user-generated content related to various fields, including AIGC design learning. Search terms were determined based on the hashtags of popular posts regarding AIGC design learning, such as "AIGC Creation", "AIGC design", "AIGC designer", "AI Design", "AI Creativity", "AI Environmental Design", and "Artificial Intelligence Art". Data collection was completed as of 19 December 2024. To ensure the quality and integrity of the data, all items were manually inspected to remove duplicates. This process resulted in a final dataset consisting of 9992 entries, with 2049 titles, 2047 post contents, and 5896 comments.

2.2. Data analysis

Previous research has demonstrated the utility of combining analytical methods regarding word cloud graphics to identify the most influential topics and sentiment analysis to assess positive or negative feelings [16]. In this study, word cloud was also used to visually represent the frequency and importance of words within the posts and comments related to AIGC design learning on the Chinese social media platform for understanding creators' perceptions. To better apply text mining, the most used words were further divided into thematic clusters, which will be explored in the subsequent analysis to uncover the underlying meanings and relationships within each theme. For conducting text mining, co-word analysis, and SNA have been used to explore specific fields. For example, Hosseini et al. [17] used co-word and SNA to visualize the thematic clusters and to understand the relationships between different concepts and the overall knowledge structure. Liu et al. [18] utilized text mining to extract the most frequently used keywords, co-word analysis to explore the relationships among these keywords, and SNA to understand the development of themes and topics. In addition, sentiment analysis serves as an effective approach for analyzing the sentiment trends of posts and comments on Xiaohongshu, as well as the sentiments from different perspectives [19,20].

Accordingly, this study uses a mixed-method approach integrating word cloud, social network, co-word, and sentiment analysis. Word cloud is adopted to identify the key concepts and themes that were most prominent in creators' discussions. SNA was used to reveal a complex web of relationships among various keywords in this study. Co-word analysis is applied to show central concepts, their connections and clusters of related terms. Sentiment analysis is adopted to comprehensively understand the creators' attitudes related to AIGC design learning.

An online data analysis software called SPSSAU was employed for in-depth text analysis of the collected content. By generating word clouds from the titles, contents, and comments using SPSSAU, researchers can identify keywords and themes within the dataset. This technique visually represents the frequency of words, with more frequently mentioned words appearing larger in the word cloud. Thus, researchers can quickly identify the most prominent topics and concepts related to AIGC design learning, which helps in understanding the overall focus and the most-talked-about clusters among Xiaohongshu users.

In previous research, sentiment analysis has been conducted to categorize the content of posts on online forums into four types: very negative, moderately negative, very positive, and moderately positive [21]. This indicates that in the relevant research field, this four-tier sentiment classification is a commonly used method, which has a certain degree of rationality and universality. Drawing on previous studies, this paper adopts a four-tier sentiment classification (positive, moderately positive, moderately negative, negative). In terms of setting the thresholds, this study uses the SPSSAU software for sentiment analysis of the posts and comments. The software compresses the sentiment scores into a range between -1 and 1 and determines the sentiment direction based on these scores. Specifically, when the sentiment score is in the range of $[-1, -1/3)$, it is judged as negative sentiment; when it is in the range of $[-1/3, 0)$, it is judged as moderately negative sentiment; when it is in the range of $[0, 1/3)$, it is judged as moderately positive sentiment; when it is in the range of [1/3, 1], it is judged as positive sentiment. If there is no score, it means that the word is not included in the sentiment dictionary, and it will be defined by the researchers themselves. It calculates the scores using a combined sentiment dictionary that includes approximately 130,000 words from sources such as BosonNLP, National Taiwan University, Tsinghua University, and CNKI. The sentiment direction of keywords is subjective. Generally, a negative score indicates negative sentiment, a positive score indicates positive sentiment, and the closer the score is to 0, the weaker (more neutral) the sentiment direction.

Regarding the sarcastic and ambiguous expressions commonly found in social media texts, it conducts a comprehensive analysis of vocabulary, syntactic structures, and contextual contexts. For ambiguous expressions, the software resolves the ambiguities based on the expression habits and semantic associations within the domain, striving to accurately determine the sentiment orientation and ensure the reliability of the analysis results. After the analysis and judgment by the software, manual inspection is also carried out to reduce misjudgments regarding common sarcasm or contextual ambiguities.

3. Results

3.1. Word cloud analysis of creators' perceptions regarding AIGC design learning

In response to RQ1, the word cloud, which showcases the top 100 words, visually represents the frequency of words within creators' discussions related to AIGC design learning on a social platform (see **Figure 1**). The word cloud clearly shows that terms such as "AIGC," "Design," "Learning," and "Creativity" are among the largest and most central words. It suggests that creators view AIGC as a tool that either enhances or is closely associated with creativity in the design process. Other words like "Tools," "Model," and "Midjourney" are also visible in the word cloud. This further emphasizes the practical applications and specific tools that are of interest to the creators.

To better understand creators' most discussed words, this study also classified thematic clusters of creators' perceptions focused on AIGC design learning as follows:

Tools and Technical Foundations for AIGC design: Words like "Midjourney (MJ)", "Stable Diffusion (SD)", and "AI" are highly visible. These are important tools in the AIGC design field. Midjourney and Stable Diffusion are powerful AIGC tools that can quickly produce high-quality images according to users' text prompts, widely applied in artistic creation and design concept generation. For example, some creators mentioned, "I tried Midjourney before. It's fun, but it has too much freedom. It's hard for the AI to follow my input to complete the corresponding composition and perspective".

Stable Diffusion, on the other hand, is an open-source text-to-image generation model with high customizability and expandability. As one creator said, "After learning Stable Diffusion, it solved most of my problems. It has a local redrawing function, which allows me to modify a small part of the original image for creative changes while maintaining the original perspective and composition. It can also directly turn line drawings into renderings. Moreover, it has LoRA (extension model). When I don’t know how to describe the desired effect, I can download LoRA templates online. There are many pre-trained architectural rendering templates. Adding these templates to my prompts makes the output more like commercial renderings, which is very helpful for students who have rough models and want to see the final effects.”

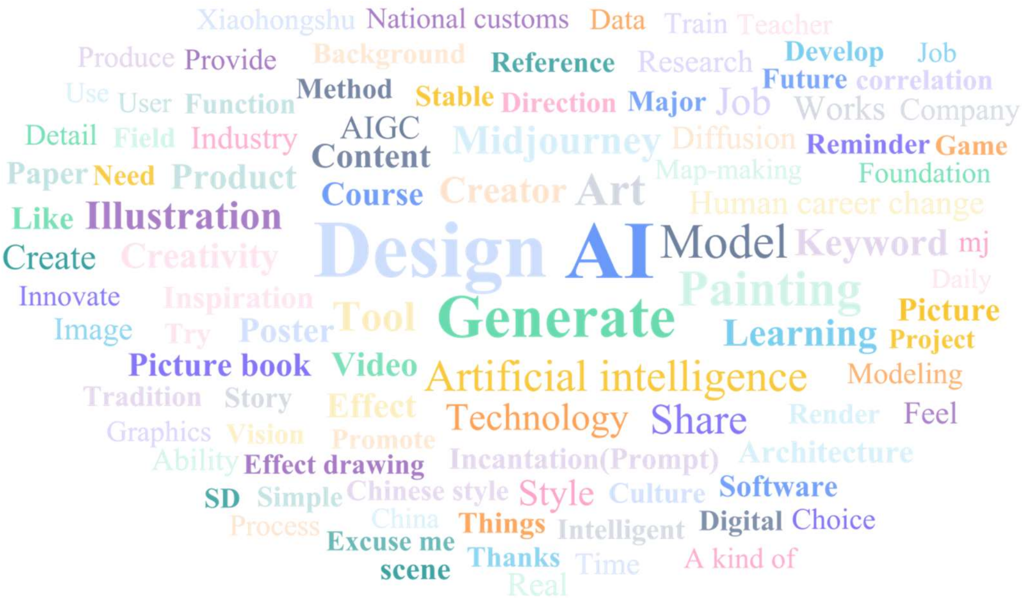

Figure 1. Word cloud of the top 100 words in creators’ discussions related to AIGC design learning.

In addition, the co-existence of “Course” and “Share” indicates that users are eager to learn how to use these tools. The mention of “Train” and “Software” implies a demand for step-by-step instructions on using AIGC-related software, as users seek practical guidance and experiences from others. Words like “Foundation”, “Map-making”, “Modeling”, and “Render” demonstrate that creators attach great importance to these aspects which are fundamental to the operation of AIGC technologies and crucial for the generation of high-quality AIGC-created images.

Application Domains of AIGC design: Terms such as “Illustration”, “Picture book”, “Poster”, “Game”, and “Scene” are present in the word cloud. This reveals that AIGC-generated images are widely used in multiple design domains. Each of these fields has its own requirements, and the application of AIGC in them showcases the technology’s adaptability.

Cultural Elements Used in AIGC: The appearance of “Chinese-style” and “Chinese culture” is significant. It reflects a trend of integrating Chinese cultural elements into AIGC design. This not only enriches the cultural connotation of the design works but also meets the cultural preferences of users. Creators might use AIGC to create illustrations with traditional Chinese patterns or game scenes inspired by Chinese mythology.

Semantic Nuances in AIGC Terminology: The term “咒语 (ZhouYu, Incantation)” is a fascinating keyword. In Chinese culture, “ZhouYu” is regarded as a word or a series of words believed to hold magical power. Reciting specific “ZhouYu” was thought to bring about particular effects in real-life scenarios, influencing supernatural beings or natural objects, with its power said to be able to affect various things like melting metal, breaking wood, or drying up water. In the AIGC field, “Prompt” shares a similar “magical” property. A “Prompt” is a text input provided by users to AIGC models, acting as a set of instructions or a description that guides the generation of specific content, such as images, texts, or code. When users input a specific “Prompt” into an AIGC model, it can generate remarkable content, similar to the purported effects of “ZhouYu”. However, the key difference lies in the medium. “Zhouyu” was supposed to influence real-world objects through spoken or written words in real-life, while a “Prompt” creates virtual design works in a digital realm, like generating images from text in “text-to-image” functions in AIGC design. Another important function in AIGC design is “image-to-image” generation. By providing a reference image (padding image), users can generate design works with similar styles, actions, or characters. This concept is analogous to the Chinese “FuZhou” (符咒), where drawing specific patterns or lines was believed to evoke mysterious powers. In the Chinese AIGC design learning community, people often share their “ZhouYu (Prompt)” experiences. They exchange information about positive and negative prompts, as well as details regarding the models, LoRAs used for image generation and sampling methods to ensure high-quality output results. This indicates that “ZhouYu” in this context is an adaptation of the Chinese language to the new concept of “Prompt” in AIGC, embodying the cultural-linguistic integration in the development of new technologies. This semantic difference is intriguing, as it could hint at the cultural adaptation and reinterpretation in the AIGC field. Such adaptation indicates how new technologies are being integrated into different cultural contexts, ultimately leading to unique semantic shifts. This semantic shift has significant impacts on AIGC workflows and community practices. In the AIGC design learning process, people often share positive and negative prompts, as well as details like the models and LoRAs used for image generation to ensure good output results. For instance, some creators shared their experiences related to “ZhouYu” and “Prompt”.

> One said, “I once shared an operation activity page designed with the help of Midjourney. The client was very satisfied with the result. Many friends asked me for the ‘ZhouYu’ and requested a tutorial. You can check the pictures carefully, and I’ve summarized the steps in the following images.”
>
> Another creator said, “Today, I’m sharing a collection of over 300 Midjourney prompts that I painstakingly organized. It includes basic commands, settings, suffix parameters, image-quality improvement prompts, and color prompts. There are too many prompts, so I’m only releasing a part of them here. I’ve basically organized all the common categories.”

Generally, in the AIGC design learning community in the Chinese context, “ZhouYu” and “prompt” are synonyms when it comes to sharing AIGC design learning tutorials. They play a crucial role in promoting the exchange of AIGC design knowledge and the sharing of experiences among creators.

AIGC design methods: A significant number of people are interested in the term “Method”, which pertains to using AIGC for creation. Since AIGC design is a relatively new discipline, a comprehensive and well-established set of learning methods has not emerged yet. By analyzing people's comments, AIGC design learning methods such as case-based learning, situational experience, and project-based practice can be identified. However, these methods are still in the exploratory stage and require further exploration to be refined.

Creativity and Innovation in AIGC Design: The frequent mention of words related to creation, such as "Creativity", "Inspiration", "Create", and "Innovation", indicates several significant clusters within the AIGC design context. Perhaps due to the fact that AIGC is capable of surmounting the limitations in design and painting techniques, thereby enabling ordinary individuals to produce professional-level design works, people's focus has veered towards ways of creating more innovative works. Users are not merely satisfied with basic AIGC applications but are eager to push the boundaries and explore new creative possibilities. However, while the enthusiasm for creativity and innovation is evident, these aspirations may face challenges in full realization, which could limit the ability of creators to turn their innovative concepts into tangible designs. AIGC creators may encounter obstacles in translating their creative ideas into practical designs due to technical limitations, insufficient tool knowledge, or the requirement for more advanced skills.

Future-oriented Perspectives in AIGC Design for Professional Development: Considering the future-oriented clusters identified from the word cloud, words like "Human career change", "Works", and "Job" stand out prominently. This indicates that individuals are interested in learning AIGC-related skills, and many are even considering switching careers to enter this emerging field. The high frequency of the appearances of "Industry", "Demand", and "Future" shows that they understand the need to equip themselves with competitiveness to meet industry needs for the future development of AIGC design.

3.2. Social network analysis and co-word analysis of creators' perceptions regarding AIGC design learning

To address RQ2, the strength of the links between keywords in the SNA provides valuable information about the relationships between different concepts. As depicted in **Figure 2**, strong links indicate a high degree of association, while weak links suggest a more tenuous connection.

In the SNA graph regarding AIGC design learning, node sizes, color saturation, and thickness of the lines serve as an intuitive visual cue for centrality, co-occurrence strength, and the relationships among different concepts. Larger nodes represent concepts with higher centrality. For example, the "AI" node stands out with its relatively large size. It has a frequency of 3475, which is a clear indication of its significance. This indicates that "AI" plays a central role in the AIGC design learning network. It has a high degree of connection with other concepts, acting as a crucial hub.

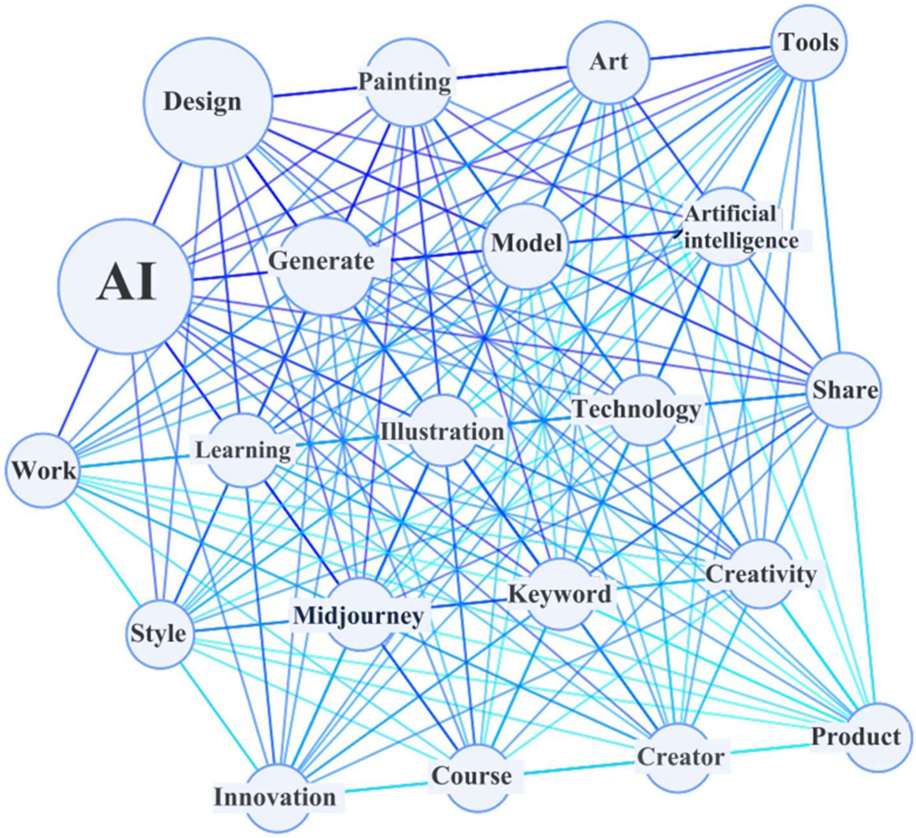

Figure 2. The relationship among different concepts related to AIGC design learning in the SNA graph.

Darker and thicker lines signify a higher frequency of co-occurrence among keywords such as “AI”, “Design”, “Generate”, “Learning”, and “Work”, indicating a stronger interconnection. This is probably because within the realm of AIGC, AI serves as a transformative force within the design process. The connections imply that creators are interested in learning the practical application of AIGC to be more competitive in future work. Creators are increasingly delving into how AI can present new design possibilities, automate repetitive tasks, and inspire innovative design concepts, thus resulting in their close association within discussions.

In the SNA graph, “AI”, with a frequency of 3475, demonstrated a strong co-occurrence relationship with “Design” for 430 times, highlighting the close integration of AI in design discussions. This indicates that creators frequently consider how AI technologies can be applied in design. In addition, the relatively high co-occurrence of 375 between “AI” and “Generate” showed that creators often associated AI with the generation process in AIGC design.

“Design”, occurring 3232 times, also holds a central position in the network. Its strong connections with terms such as “Share”, “Generate”, and “Art” highlight its importance within the AIGC context. The strong connection with “Share” (co-occurring 290 times) suggests that creators in the AIGC design community highly value the dissemination of design ideas and works. The 284 times co-occurrence with “Generate” and 290 times with “Art” imply that AIGC technologies are significantly influencing the design generation process for creating aesthetic work.

The co-occurrence of “Artificial Intelligence”, “Art”, “Model”, “Share”, “Tools”, and “Technology” is also notable, with relatively dark and thick lines linking them.

This can be attributed to the fact that AIGC tools, powered by agent technologies, are mainly used for generating various design outputs, such as paintings, illustrations, and products. Creators are keenly interested in sharing the course on how to use AIGC tools and understanding the underlying AI-based generation mechanisms, which explains their frequent appearance together in the discourse. When learners find posts related to AIGC design (e.g., courses demonstrating the utilization of Midjourney) that exhibit remarkable creativity, distinct styles, or innovative design outputs in diverse forms, they frequently leave comments asking the creators to provide the corresponding keywords, which may enable them to replicate the same works using those identical keywords.

Conversely, lighter and thinner lines, such as those around terms like “Course” and “Style”, indicate a lower frequency of co-occurrence. “Course” might have weaker connections as the educational aspect related to AIGC design is still emerging and not as deeply integrated into the core discussions about the practical application and technological aspects of AIGC. “Style”, while relevant, might be considered more of a subjective and secondary factor when initially learning the courses of AIGC design.

3.3. Sentiment analysis of AIGC design learning and cases

To gain a deeper understanding of the development trends in the AIGC design learning clusters as reflected by the word cloud, this study conducts sentiment analysis. In response to RQ3, this sentiment analysis offers valuable insights into users’ attitudes, which could be categorized into four main types: positive, moderately positive, moderately negative, and negative.

Regarding the sentiment orientation, among all the data (i.e., 9992 posts and comments), the proportion of moderately negative sentiment was the highest, reaching 47.94% (4790 instances), while the negative sentiment had the lowest proportion, at 1.78% (178 instances). The high proportion of moderately negative sentiment can be attributed to several factors. On one hand, in the era dominated by AI, designers are likely anxious about being replaced by AI, fearing potential job losses, or disruptions to their original career development paths. However, despite these concerns, many are actively embracing and learning AIGC design methods, and adjusting their career directions accordingly. On the other hand, some individuals find that the actual effects of AIGC design do not meet their expectations. They often need to invest additional effort in manual adjustments, which leads to feelings of frustration and contributes to the moderately negative sentiment. The positive sentiment accounted for 35.70% (3567 instances), and the moderately positive sentiment made up 14.58% (1457 instances), as users likely recognize the potential of AIGC to revolutionize the design process, bringing about new creative possibilities, increased efficiency, and enhanced productivity.

As shown in **Figure 3**, the waterfall diagram shows trends of different sentiments among the above classified clusters in AIGC design learning. The vertical axis represents cluster frequencies, indicating the number of posts or comments for each cluster, which reflects the frequency of occurrence of content related to each cluster. The horizontal axis shows the sentiment proportions of four categories: positive, moderately positive, moderately negative, and negative.

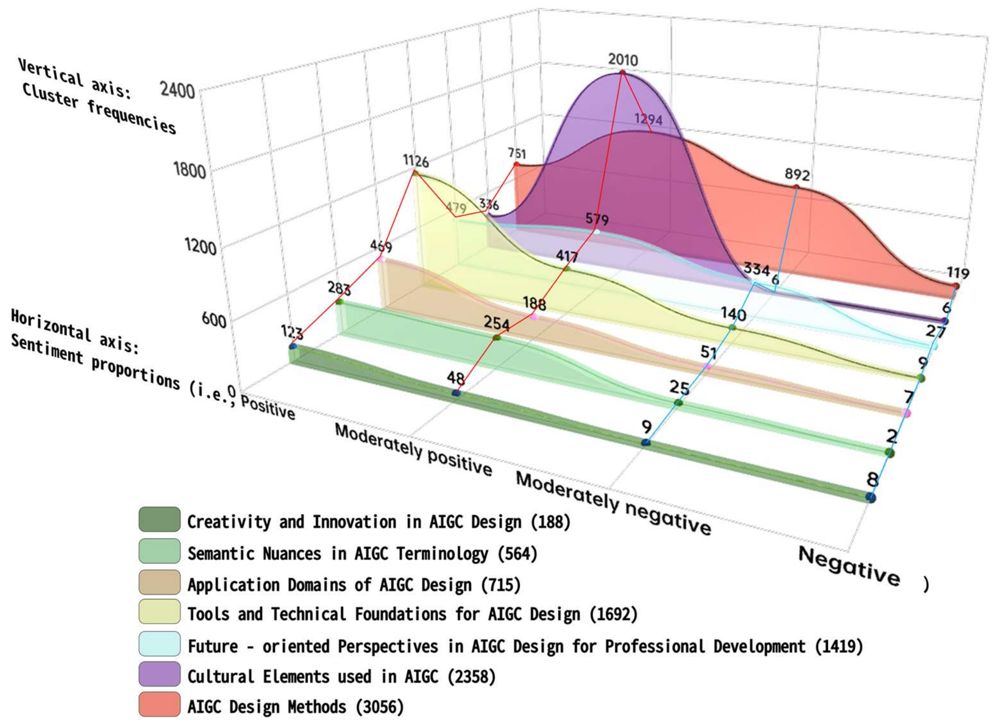

Figure 3. Trends of sentiment and the number of different clusters in AIGC design learning.

Each color in the figure represents a different cluster in AIGC design learning, including Creativity and Innovation in AIGC Design; Semantic Nuances in AIGC Terminology; Application Domains of AIGC Design; Tools and Technical Foundations for AIGC design; Future-oriented Perspectives in AIGC design for Professional Development; Cultural Elements used in AIGC; AIGC design methods. This visualization aids in observing how the sentiment distribution varies across different clusters in AIGC design learning and also presents the relative frequencies of these clusters. The "AIGC design methods" accounted for the largest proportion (30.56%) among all clusters, with 3056 instances. This high prevalence might indicate that users are highly interested in learning about practical design methods and new learning methods in the AIGC field. On the contrary, "Creativity and Innovation in AIGC design" had the smallest proportion, only 1.88% (188 instances), suggesting that this cluster may receive relatively less attention than other discussions. The specific data, analyses, and cases for these different clusters are presented below.

a) Tools and technical foundations for AIGC design.

In the cluster of tools and technical foundations for AIGC design (1692 instances), positive sentiment, accounting for 66.55% (1126 instances) of the related posts and comments, often centered around sub-dimensions such as the ease of use of new AIGC design tools, their ability to speed up the design process, the high-quality outputs they can generate, and the availability of useful tutorials for learning these tools. This shows that creators highly value the practical benefits these tools bring to their design work. Examples are as follows.

> "Designers are all crying out about losing their jobs and switching careers. However, AIGC technology makes design more efficient. It brings not only negative impacts but also more opportunities to the design industry."

> "Having grown accustomed to the exquisite AI images with large apertures and perfectly adjusted colors, these AI pictures that are closer to real-life quality are almost indistinguishable."

Negative sentiment (0.53%, 9 instances) and moderately negative sentiment (8.27%, 140 instances) mainly stemmed from sub-dimensions like occasional technical glitches or bugs in the tools, difficulties in integrating the tools with existing design workflows, high system resource requirements that cause slowdowns, lack of AI specialized knowledge background for designing, and complex licensing or subscription models. This indicates that although the overall perception is positive, there are still areas where tool developers need to focus on improving.

> "I really want to smash my computer. It's so hard to control. Generating 3D models from line drawings is extremely difficult. It often fails to generate, and the large-scale model can't be switched either."

> "Anyway, there are all kinds of problems. It always fails to generate images. It keeps saying there are continuous errors. Ever since I downloaded the large-scale model and LoRA, there have been more and more problems."

b) Application domains of AIGC design.

Regarding application domains of AIGC design (715 instances), positive sentiment, at 65.59% (469 instances), was associated with sub-dimensions including the wide range of industries where AIGC design can be applied, the ability to create unique and eye-catching designs in these domains, the increased creativity enabled in various application areas, and the potential for opening up new business opportunities.

> "My friend is a new Chinese-style AI blogger. It's a blue ocean! They've gained 30,000 followers!"

> "After using Midjourney for nearly a year, going from scratch to where I am now, the deepest feeling I have is that it's incredibly addictive! Once you start using it, you simply can't do without it! No matter which industry you're in, you can easily complete all complex design frameworks. Whenever you're out of creative inspiration, it always gives you some unexpected surprises!"

Negative sentiment (0.98%, 7 instances) and moderately negative sentiment (7.13%, 51 instances) were related to sub-dimensions such as limited acceptance of AIGC-designed work in some conservative industries, concerns about the quality consistency of AIGC-generated outputs with real-world scenes, lack of standardization in applying AIGC across different domains, and potential legal or ethical issues in certain application scenarios. This suggests that while the application prospects are promising, there are barriers to full-scale adoption.

> "Although AI has developed, the gaming industry is getting tougher. Those companies that laid off most of their artists didn't help their bosses earn more. Instead, they're even at risk of facing homogenization and going out of business."

c) Cultural elements used in AIGC.

In the cluster of incorporating cultural elements in AIGC (2358 instances), positive sentiment, 14.25% (336 instances), is mainly associated with numerous Chinese-characteristic elements. It also contributed to clusters such as the discovery of new cultural expressions through AIGC, the empowerment of local cultures on a global stage, the innovative combination of different cultural elements, the use of AIGC to preserve endangered cultural forms, and the educational value of cultural

AIGC designs. This indicates a high level of enthusiasm for the cultural potential of AIGC.

> "In the future, there could be an AI style school. The main reason is that AI paintings are so distinctive."

Moderately positive sentiment, making up 85.24% (2010 instances), was linked to sub-dimensions like the successful incorporation of traditional cultural elements such as "Chinese national style", "new Chinese style", "Chinese retro style", "Splash-ink style", "Digital Humanities", "Intangible Cultural Heritage", "Fairyland", "Eastern Aesthetics", "Ink-wash Painting", "Poetry", and "Ancient Style". These elements not only endow AIGC works with a unique Chinese charm but also meet the aesthetic needs for the modern interpretation of traditional culture.

> "I just really love the details, which are super suitable for making Chinese-style posters."

Negative (6 instances) and moderately negative sentiment (6 instances) mainly focus on the improper use or misunderstanding of cultural elements. Some AIGC works may simply stack Chinese-characteristic elements without in-depth understanding of the cultural connotations, resulting in works that seem rigid and superficial. In some cases, when integrating different cultural elements, a lack of balance leads to style conflicts. Moreover, the distortion or abuse of traditional cultural elements in some works may cause disputes in cultural identity. Improper use of intangible cultural heritage elements without following relevant cultural norms and intellectual property rights can also trigger negative comments. Additionally, the over-reliance on AIGC technology in generating cultural elements and the lack of manual artistic processing make the works seem soulless.

> "The pictures created by AI are nice, but there always seems to be a familiar feeling. It's like a mix of many artists' styles, and finally it forms its own style. Although humans also follow this path, AI is more rigid."

d) Semantic nuances in AIGC terminology.

In the cluster of semantic nuances in AIGC terminology (564 instances), "Prompt (i.e., 咒语, ZhouYu)", "Keyword", and "Training LoRA (i.e., 炼丹, Liandan)" are of great significance. Regarding "炼丹 (Liandan)", in Taoism, it refers to two types of practices: refining external elixirs and internal elixirs. External elixirs were made by burning materials in a furnace to create magical pills. People believed that consuming different pills could achieve various specific effects. Internal elixirs, on the other hand, considered the human body as a furnace and focused on cultivating one's own essence, qi, and spirit. "Training LoRA" in AIGC is similar to refining external elixirs. Just as Taoist alchemists carefully selected and combined materials in the furnace to create elixirs with specific properties, in AIGC, when training a LoRA, practitioners adjust various parameters and use specific data. They aim to optimize the model to achieve more powerful support, control the consistency of designed roles, and obtain customized model effects, much like how alchemists strived for the desired properties in their elixirs.

> "Newbie's Guide to Training Models | Basic Notes on Stable Diffusion (For Personal Use)."

> "Recommended Training LoRA Models. Ensure You Train Your First Model Successfully."

Positive sentiment, 50.18% (283 instances), was associated with sub-dimensions including the excitement of learning new AIGC-related terms, the clarity of these terms in communicating design ideas, the development of a shared vocabulary within the AIGC design community, the use of these terms to explore new design concepts, and the ability of these terms to bridge the gap between different design disciplines. It reflects a positive attitude towards language development in the AIGC field. Positive sentiment often centres around the role of these terms in precisely guiding AI creation. When creators master effective "Prompt" and "Keyword" combinations and get amazing works generated by AI, they affirm the value of these terms. Recognition of "Training LoRA" technology is also based on its ability to enhance the model's personalized performance and provide more creative possibilities.

> "I tested the effects of the new version of the software. Sure enough, it's quite amazing. Here are the key prompts for image generation."

Negative sentiment (0.35%, 2 instances) and moderately negative (4.43%, 25 instances) were related to sub-dimensions such as the confusion caused by the rapid evolution of AIGC terms, the lack of standardization in the use of these terms, the difficulty for non-technical users to understand complex AIGC jargon, the inconsistent interpretation of certain terms in different contexts, and the perception that some terms may be over-hyped. For novices, the usage rules of "Prompt" and "Keywords" and the complex technical principles of "Training LoRA" are hard to grasp, resulting in poor creation results. In addition, concerns regarding copyright issues in the AIGC design process have also emerged. There is a risk that some individuals may use others' images to train LoRA models without proper authorization, which is a serious violation of copyright. Moreover, the generated characters often have problems with hands and limbs, such as deformities, which affect the quality and usability of the final design. To address these issues, certain AIGC design methods have been proposed. For instance, the use of Control Net can help improve the control over the generation process and potentially reduce the occurrence of abnormal body part generation. When generating images from text, it is crucial to pay attention not only to positive prompts but also to negative prompts. Negative prompts can be used to exclude unwanted elements or characteristics from the generated images, thus enhancing the quality and accuracy of the output. However, the implementation of these methods also faces challenges, such as the need for users to have a good understanding of how to use them effectively. This shows that there are minor yet significant challenges in the semantic development of AIGC, as well as in the ethical and technical clusters of its design process.

> "AI still lacks legal copyright constraints. It's clearly based on pirating the works of established designers and illustrators."

e) AIGC design methods.

In the dimension of AIGC design methods (3056 instances), elements like "Workflow", "Process", "Valuable content", "Steps", "Courses", "Understanding", and "How to" frequently appear. "Workflow" in AIGC design, closely related to AI agents, generally refers to the sequence of operations and interactions using AI agents to complete design tasks. Typically, the workflow starts with problem definition, where designers clarify the design goals and requirements. Then, relevant data is collected, which could include reference images, text descriptions, and style guides. Next, the AI agent is fed with the appropriate "Prompt" and "Keywords" based on the collected data to generate initial design drafts. After that, designers review and evaluate the drafts, providing feedback to further refine the AI-generated content through additional training or parameter adjustments. Finally, the refined design is finalized and presented.

"Overall idea: First, use image-to-image generation to create the main character; second, generate the flower background; third, synthesize the generated character and background in PS; fourth, put the synthesized image back into SD for restoration; fifth, draw cards again and put them into PS for image retouching; sixth, do the layout. For detailed parameters, see the text and pictures."

Positive sentiment, 24.57% (751 instances), also contributed to clusters such as the inspiration drawn from innovative methods, the ability of these methods to cater to different learning styles, the improvement of design skills through hands-on AIGC design training, and the long-term benefits of mastering these new methods for career development. Moderately positive sentiment, 42.34% (1294 instances), was linked to sub-dimensions like the novelty of new AIGC design methods, the potential of these methods to unlock new levels of creativity, the availability of online courses for learning these emerging approaches, the practical case studies demonstrating the effectiveness of the methods, and the community support for learning and sharing these design methods. It indicates that users see value in the new design paradigms. For example, some users are excited about the prospect of using generative design methods in their projects.

> "I recently made a picture book and have integrated the process for you! If you want a very detailed work process, please send me a private message in the comments. I'm already organizing the document workflow for everyone."

However, moderately negative sentiment, at 29.19% (892), was associated with sub-dimensions including the steep learning curve of new design methods, the lack of in-depth practical guidance in learning materials, the mismatch between learning content and real-world design requirements, the high cost of enrolling in quality AIGC design courses, and the uncertainty about the long-term viability of some emerging learning approaches. The rapid evolution of AIGC design methods means that the knowledge taught in courses may quickly become outdated, leaving learners feeling that their efforts are in vain.

> "Currently, I've found that the most profitable thing in this area is selling courses. Some charge exorbitantly high prices, while others offer them at relatively lower, yet still costly rates".
>
> "This time, it took about 2–3 days to make the picture book with Midjourney. There were a lot of places that needed manual modification. I really can't make a set of AI-generated picture books in two hours. During the process this time, there were often cases where the pictures couldn't be generated or the pictures deviated too much. After several hours, I was still generating pictures non-stop. I even wished I could just draw them by hand, which might have been faster".

f) Creativity and innovation in AIGC design.

Regarding creativity and innovation in AIGC design (188 instances), positive sentiment, 65.43% (123 instances), was associated with sub-dimensions such as the ability of AIGC to generate novel and unexpected design ideas, the stimulation of out-of-the-box thinking in designers, the creation of unique visual identities through AIGC, the use of AIGC to push the boundaries of traditional design, and the enhancement of team creativity through AIGC-enabled brainstorming sessions. It reflects that users highly value the creative potential of AIGC.

> "Once again, I'm amazed by the creativity of AI!"
>
> "In the future when robots can paint, no matter what career your child will pursue, cultivating creativity and aesthetic comprehension is an investment that will benefit them for life. As we've all probably heard, many jobs will disappear in the future. When today's children grow up, what they actually need most is outstanding creativity, which is a hard-to-acquire ability that big data and AI lack. Besides this hard power of outstanding creativity, there's also a very important soft power, which is excellent aesthetic ability."

Negative sentiment (4.26%, 8 instances) and moderately negative sentiment (4.79%, 9 instances) were related to sub-dimensions like the fear that AIGC may lead to the lack of true creativity by relying too much on algorithms, the blow to the original designers' enthusiasm by the rapid speed of AIGC's work generation, the perception that AIGC-generated ideas may be formulaic, the concern that it may stifle individual design styles, the difficulty in protecting creative AIGC-generated works from being copied, and the worry that over-reliance on AIGC may reduce human creative efforts in the long run.

> "I don't quite understand why artificial intelligence has to focus specifically on the creative industries. Moreover, no matter how powerful AI's big-data computing is, it still lags far behind the human brain in terms of precise humor, wittiness, and logical yet imaginative thinking."
>
> "If you just switch careers as soon as AI arrives without even trying to adapt, you'll always be left behind. Not so many people have the energy and money to start their own businesses and become independent producers."

g) Future-oriented perspectives in AIGC design for professional development.

From the perspective of future-oriented perspectives in AIGC design for professional development (1419 instances), moderately positive sentiment, 40.80% (579 instances), was linked to sub-dimensions such as the potential for career advancement through AIGC skills, the emergence of new job roles in the AIGC design field, the ability to stay competitive in the job market with AIGC knowledge, the opportunity to work on cutting-edge projects using AIGC, and the long-term growth prospects in the AIGC-related industries.

> "Is there any company recruiting in this field? I'd like to recommend myself."
>
> "I really like your Chinese-style sense. I'm currently using AIGC, and I hope to join the group to communicate with everyone."

Positive sentiment, 33.76% (479 instances), also contributed to clusters such as the chance to collaborate with international AIGC design teams, the potential for starting one's own AIGC-focused business, the ability to influence the future direction of the design industry through AIGC, the access to global design resources enabled by AIGC, and the development of leadership skills in the AIGC design space.

> "Not bad. Let's have a friendly discussion. Why do you want to reduce the use of AI? Is it because the click-through rate of AI-generated content is not high? Or is there some other reason?"
>
> "I've looked into it. Training with AI really takes a toll on the computer, and I haven't seen many job openings either. Before, I did see some requirements like drawing a certain number of pictures per day."

However, moderately negative sentiment (23.54%, 334 instances) and negative sentiment (1.90%, 27 instances), were associated with sub-dimensions including concerns about job displacement due to AIGC automation, the uncertainty of future AIGC regulations affecting career stability, the lack of clear career paths in the rapidly evolving AIGC field, the potential for skills to become obsolete quickly, and the difficulty in keeping up with the fast-paced AIGC technological changes.

> "I think what the blogger said makes a lot of sense. Nowadays, whenever you scroll through, you can see people saying that designers are about to lose their jobs, which makes new graduates extremely anxious."
>
> "AI definitely can't replace designers at present. Instead, it affects my working hours. The stuff it renders... is not even as good as just finding some materials."

In conclusion, the sentiment analysis reveals that the majority of users on Xiaohongshu have a positive or moderately positive attitude towards AIGC design learning. However, different clusters of AIGC design evoke diverse sentiment responses. The clusters related to tools, applications, and cultural elements generally receive more positive feedback, while the areas of design methods and future-oriented perspectives show a more complex sentiment distribution, with a relatively higher proportion of moderately negative sentiment. These findings provide valuable insights into the perception and attitude of the AIGC design learning community on Xiaohongshu, which can be useful for further research and development in the AIGC design field, as well as for educators and industry practitioners to better understand users' needs and concerns.

h) AIGC design ethics.

Regarding AIGC design ethics, concerns about ethics and copyright have been raised in various clusters. Negative sentiment sub-dimensions are more numerous. One significant concern is copyright infringement. As AIGC often generates content based on large datasets, there are worries that it may use copyrighted materials without proper authorization, leading to legal disputes. Another is bias in AI-generated content. The models may inherit biases from the training data, resulting in discriminatory or unfair designs. The lack of transparency in AIGC algorithms is also a worry. Users are concerned that they cannot understand how the AI makes decisions, which makes it difficult to hold anyone accountable for unethical results. Additionally, the potential for misuse of AIGC, such as creating fake or misleading designs for malicious purposes, is a major ethical concern. There are also concerns about the impact on human creativity and employment. Some worry that over-reliance on AIGC may stifle human creative efforts and lead to job losses in the design field. Finally, the issue of data privacy in AIGC is a significant negative sub-dimension. The collection and use of user data during the AIGC design process may pose risks to personal information security.

"In an era where technology and art converge, controversies regarding technology, law, and ethics are on the rise. The relationship between humans and artificial intelligence may become a proposition that urgently needs to be pondered in the post-human era. Humans should actively examine the limitations of artificial intelligence and guide its development within the ethical track with positive values".

"We need to consider whether there is a risk of privacy leakage when using AIGC. For example, the possibility of facial recognition being hacked, or the theft of images for profit through infringement".

3.4. Comparative analysis between AIGC's impact on design learning and traditional design tools

The advent of AIGC technology has introduced a new paradigm in the design industry, presenting both opportunities and challenges when compared to traditional design tools. Future design learning scenarios demand a blend of diverse knowledge and skills. However, traditional design tools have often posed challenges in this regard. Similar to the issues in traditional interdisciplinary cooperation, in the context of design learning, traditional tools such as hand-drawn sketches and handmade models limit the learning process [4]. Due to their nature, students may struggle to quickly translate their creative ideas into visible forms.

In contrast, AIGC presents a promising solution to transform design learning. As demonstrated by Midjourney in design innovation [10], AIGC can rapidly generate multiple design concepts. In a design learning environment, this means students can quickly visualize different interpretations of their ideas, which not only saves the students' effort in the initial "shape-making" stage but also exposes them to a wider range of design possibilities, stimulating their creativity and promoting a more in-depth exploration of design concepts.

For example: the creators expressed that

"I was really startled by the renderings made by AI. The traditional design workflow simply can't compete with AI. Just casually give a model to AI, and it can generate an image within a few minutes."

"When I used a sketch to generate a product rendering—the design of a game controller. Without using AI, traditional rendering would take 1 to 2 h. With AI, it was done in just 3 min. Let me see who else can't use AI to assist in industrial design. You can send a private message to the background to get the AIGC industrial design materials integration package for free."

3.5. Case studies of designers who have successfully integrated AIGC into their workflows

In the exploration of integrating AIGC into design workflows, several designers shared their experiences, offering valuable insights into the practical application of AIGC in different creative processes.

a) Case 1: Digital humanities research-transforming ancient paintings from 2D to 3D.

Data collection: To initiate the transformation of ancient paintings from 2D to 3D using AIGC, the first step was data collection. A comprehensive set of image data of ancient mountains and rocks was gathered. Each data point was carefully annotated. This meticulous annotation process was crucial as it ensured the high-quality of the training set, which served as the foundation for subsequent AI-based operations.

Training Model: After data collection, the Kohya software was utilized to train the LoRA model. This trained model was then employed in conjunction with SD WebUI to generate images. The combination of these tools allowed for the initial generation of visual content that could potentially be transformed into 3D models.

Style transfer: From the images generated in the previous step, high-quality ones were selected. These images were then processed through Qiyu AI for style transfer. This step aimed to enhance the visual appeal of the images and make them more suitable for the subsequent 3D conversion process.

3D Processing: Wonder3D and Meshy were the key tools in converting the 2D images into 3D models. However, this process was not without challenges. Inferring the backside details and processing complex textures were the two main obstacles that needed to be overcome during this stage.

Post-processing and Revision: To refine the 3D models and ensure their realism and artistry, Blender and C4D software were used. In these applications, texture mapping was carried out, and details were refined. This post-processing step was essential for enhancing the overall quality of the final 3D models.

Exhibition: The final step involved integrating the restored 3D models into videos or Unity environments. This integration resulted in the generation of engineering files, which could be used for various purposes such as digital exhibitions or interactive experiences.

b) Case 2: Generating valuable illustrations with AI-sharing operation methods and precautions.

Some creators focused on using AI to generate valuable illustrations and shared their practical knowledge with professional peers.

LoRA Settings: Don’t set LoRA model values too high. When combining multiple LoRAs, a total value of around 0.7–0.8 is best. High values may cause style overflow, distorting the final image.

Sampling Methods: Different sampling methods give different results. Designers should try multiple methods during image generation to explore styles and pick the right one for their projects.

Redrawing Amplitude: A redrawing amplitude of about 0.5 is often good. It keeps the generated image similar to the input shape while letting AI modify the surroundings.

Width-Height Ratio: Keep the width-height ratio the same as the input image. This makes the final composition look more natural, especially with reference materials.

ControlNet Parameters: When using ControlNet, check ‘Enable’ and ‘Preview’. After uploading an image, click the small black dot by the pre-processor to preview edge recognition and ensure clear, accurate results.

Learning Resources: Check learning resources from tutorials. Many platforms like Liblib AI are based on SD. Learning SD's principles and techniques from these tutorials can boost proficiency in using such platforms.

4. Discussion

This study aimed to analyze posts and comments related to AIGC design learning on Xiaohongshu through word cloud, sentiment analysis, text mining, co-word analysis, and SNA, filling a research gap in understanding public affective tendency of AIGC in design education.

Similar to previous AIGC design-based research [2,3,10], this study also shows the significance of AIGC in design innovation and creative thinking. In addition, the positive sentiment towards AIGC in clusters like tools and technical foundations, application domains, and cultural elements in this study is consistent with the idea that AIGC can bring new opportunities and improvements in design [4,5]. Regarding the influence on users' learning and professional development, the finding that many users are interested in learning AIGC-related skills and considering career transitions in this emerging field corresponds to the general understanding from prior studies that the skill of using generative AI is an important competency to develop desired career prospects [1]. Beyond the similarities discussed above, this study also exhibits differences from previous research in terms of AIGC design ethics, research focus, and AIGC design learning sentiment distribution.

Regarding AIGC design ethics, unlike the perspectives of existing studies on professional and technical ethical issues [9], this study explores the emotional tendencies and perception of AIGC design ethics from the perspective of social media users, who are the general public using AIGC for design. It reveals the real-world concerns of ordinary users, such as their worries about copyright infringement, bias in AI-generated content, the possibility of stifling human creative efforts, and leading to job losses in the design field. This user-centered perspective provides a more grounded and practical understanding of ethical issues in AIGC design.

Regarding research focus, while some studies on Xiaohongshu data have conducted sentiment analysis, they mainly focus on topics like visual and emotional preferences of Internet-famous sites and the negotiation of travel photo authenticity [19]. This study's sentiment analysis of AIGC design learning reveals different patterns. It shows that the sentiment towards AIGC design learning is a mix of positive and moderately negative views. Positive sentiment is prominent in areas like the potential of AIGC tools, while moderately negative sentiment exists regarding design methods and ethical concerns. These findings are specific to the AIGC design learning context and have not been reported in previous sentiment analysis-based research.

Regarding AIGC design learning sentiment distribution, previous sentiment analysis-based studies on AI and design tend to focus on clusters such as the impact of AI in education, healthcare, and sustainable fashion [22–24]. This study, however, specifically targets AIGC design learning, which is a more specialized area within the broader AI design domain. It examines the sentiment of users towards learning AIGC design, including their attitudes towards different learning resources, learning methods, and the overall learning experience. Specifically, this study found that some creators expressed their positive perceptions and attitudes regarding the utilization of AIGC in healthcare-related design applications. This is consistent with the insights from previous studies [25–27], which provide valuable insights into the use of AIGC in healthcare-related design applications. For instance, creators highlighted companies that integrate healthcare-related "game-based chemotherapy recovery" applications with AI and those focusing on emotional intelligence and voice interaction. They noted that these enterprises have secured promising financing prospects. In their analysis, they pointed out that.

> "Although psychological healing products face the challenge of striking a balance between pursuing user stickiness and satisfying healing needs—users engage with these products to address psychological or emotional issues, and the ideal scenario is for them to naturally discontinue use after achieving healing, yet product growth and operation hinge on user retention and engagement—these creators still perceive AI's potential in healthcare as immense and maintain an optimistic stance."

In addition, other creators turned their attention to the advancement of healthcare-related technology and the issue of population aging, which has become more pronounced with the increase in human lifespan. They have a positive attitude about the potential of AIGC to illustrate such issues. They gave an example of using AIGC to generate relevant promotional images and provided a specific reference workflow:

> "With the help of the two great artificial intelligence tools, ChatGPT and Midjourney, a series of visual diagrams about the 'hazards of population aging' were created in less than 3 min."
>
> The workflow is as follows:
>
> "First, pose questions to ChatGPT to understand the hazards that population aging will bring to society.
>
> Second, extract the required keywords from the text generated by ChatGPT.
>
> Third, prior to sending the "Prompt" to Midjourney, supplement and refine the keywords with as much detail as possible. Midjourney will then generate four visual templates for reference based on the description.
>
> Fourth, expand the images according to specific requirements."

Some previous studies use sentiment analysis to categorize AI-related learning sentiment as positive, negative, or neutral (e.g., [22]). This study, in addition to basic sentiment classification, further divides sentiment into four levels: moderately negative, positive, moderately positive, and negative. It also explores the sentiment distribution across different clusters of AIGC design learning and reveals relationships among various keywords. This more detailed analysis provides a more comprehensive understanding of users' attitudes towards AIGC design learning.

This study extends the work of a previous study [15], which applied the Technology Acceptance Model to analyze user experience. Our research expands this analysis into the AIGC design learning domain by proposing a mechanism of "Design Outcome-Project Content Innovation-AI Technical Support".

Regarding the recommendations for educators, several practical suggestions for improving AIGC courses are as follows. First, "Design Outcome" implies presenting students with a visualized design work as an excellent example of the achievements they can attain after completing the AIGC course. This can enhance their eagerness to learn. Additionally, introducing future-oriented perspectives in AIGC design for professional development can help students recognize the benefits of mastering AIGC design for their future growth, thus stimulating their internal learning motivation.

Second, “Project Content Innovation” encourages students to consider what innovative improvements they can make to existing excellent design works to create their own designs. This involves the aspect of creativity and innovation in AIGC design. For instance, students can be guided to explore how to use AIGC to break through traditional design limitations and generate novel design concepts. It also relates to the aspect of cultural elements used in AIGC. Regarding cultural adaptation, the incorporation of Chinese cultural elements in AIGC design reflects the process of cultural hybridization. According to cultural adaptation theories, when a new technology is introduced into a cultural context, it undergoes a process of adaptation to fit local cultural values and norms. In this study, the use of terms like “Chinese-style” and “Chinese culture” in AIGC design not only enriches the design works but also demonstrates how AIGC is being adapted to meet the cultural preferences of Chinese users. This adaptation is a form of cultural expression and a means of making the technology more relevant and appealing in the local context. Educators can prompt students to think about how to incorporate the culture of their own ethnicity into the design. This not only enriches the cultural connotation of the design but also helps students develop a unique design style.

Finally, after students have a positive attitude towards learning AIGC and are internally motivated, providing AI technical support becomes crucial. This involves teaching students relevant knowledge in various aspects, such as the tools and technical foundations for AIGC design, the application domains of AIGC design, the semantic nuances in AIGC terminology, AIGC design methods, and AIGC design ethics. In the area of tools and technical foundations for AIGC design, educators can introduce different AIGC tools like Midjourney and Stable Diffusion and teach students how to use them effectively. When it comes to the application domains of AIGC design, students can be informed about the wide range of industries where AIGC is applied and the specific requirements of each domain. Regarding semantic nuances in AIGC terminology, educators can clarify the meanings and usage of terms like “Prompt” and “Training LoRA” to help students better communicate and operate in the AIGC design field. For AIGC design methods, educators can share practical design processes and case-based learning methods. In terms of AIGC design ethics, educators should raise students’ awareness of ethical issues such as copyright infringement and bias in AI-generated content. Overall, AIGC design learning follows a result-oriented Understanding by Design approach, where the desired learning outcomes guide the design of teaching content and activities.

5. Conclusion and implication

This study contributes to the existing body of knowledge in several theoretical clusters. It extends the understanding of how AIGC is perceived and used in a real-world, social media-based learning context. By analyzing the word cloud and sentiment of posts and comments, it provides a new perspective on the relationship between users and AIGC design learning. The identification of different themes in the word cloud, such as semantic nuances in AIGC terminology and the integration of cultural elements, enriches the theoretical understanding of the cultural and semantic clusters of AIGC design. These findings suggest that AIGC is not only a technological tool but also a medium for cultural expression and semantic evolution in the design field. The SNA graph, through its line color and thickness variations, vividly presents the hierarchical and associative structures among various terms. It offers valuable insights into the focal points of interest and the nature of relationships within the dynamic field of AIGC design learning, helping researchers and practitioners better understand the current landscape and trends in this area.

For educators, the results of this study can guide the development of more effective learning strategies. Since "AIGC design methods" was a major topic of interest, educators can focus on improving AIGC learning materials and courses related to these areas. They can address the issues highlighted by the moderately negative sentiment, such as the steep learning curve and the lack of in-depth practical guidance, by providing more hands-on training, updated course content, and better-structured learning resources. For the AIGC design industry, understanding user sentiment is crucial. The positive sentiment towards tools and application domains indicates that there is a market demand for further development and improvement in these areas. However, the concerns related to ethics, such as copyright infringement and bias in AI-generated content, should be addressed. Industry practitioners need to develop more ethical guidelines and technical solutions to ensure the sustainable development of AIGC design.

6. Limitation and future research directions

This study also has some limitations, which need to be addressed in future AIGC-based research. This study relied solely on data from Xiaohongshu, a Chinese-based social media platform. The findings may be limited to the specific user group and cultural context of this platform. Future research could collect data from multiple social media platforms worldwide. In addition, the study only calculated the sentiment orientation regarding AIGC design learning and did not consider other factors that might influence users' perceptions and attitudes. Future studies could prioritize gathering data on factors such as age, gender, professional background, and educational level, and conduct correlational research or other relevant investigations.

Acknowledgments: The author would like to express the sincere gratitude to the experts for the invaluable technical support. Special thanks also go to the Xiaohongshu platform and its users who shared public posts and comments related to AIGC design learning. Their contributions have been instrumental in enabling this research.

Institutional review board statement: The study was conducted in accordance with the Declaration of Helsinki. Ethical review and approval were waived for this study because the data was directly obtained from open-social platforms, anonymized, and did not involve direct testing on humans.

Informed consent statement: Patient consent was waived due to the retrospective scientific nature of this study.

Conflict of interest: The author declares no conflict of interest.

References

1. Weng X, Xia Q, Gu M, et al. Assessment and learning outcomes for generative AI in higher education: A scoping review on current research status and trends. Australasian Journal of Educational Technology. 2024. doi: 10.14742/ajet.9540
2. Huangfu J, Li R, Xu J, et al. Fostering Continuous Innovation in Creative Education: A Multi-Path Configurational Analysis of Continuous Collaboration with AIGC in Chinese ACG Educational Contexts. Sustainability. 2024; 17(1): 144. doi: 10.3390/su17010144
3. Tan L, Luhrs M. Using Generative AI Midjourney to enhance divergent and convergent thinking in an architect's creative design process. The Design Journal. 2024; 27(4): 677-699. doi: 10.1080/14606925.2024.2353479
4. Wang Y, Xi Y, Liu X, et al. Exploring the Dual Potential of Artificial Intelligence-Generated Content in the Esthetic Reproduction and Sustainable Innovative Design of Ming-Style Furniture. Sustainability. 2024; 16(12): 5173. doi: 10.3390/su16125173
5. Jiang Q, Zhang J, Wang PH, et al. Technology Acceptance and Innovation Diffusion: Are Users More Inclined Toward AIGC-Assisted Design? International Journal of Human–Computer Interaction. 2024: 1-15. doi: 10.1080/10447318.2024.2408513
6. Huang KL, Liu Y chen, Dong MQ. Incorporating AIGC into design ideation: A study on self-efficacy and learning experience acceptance under higher-order thinking. Thinking Skills and Creativity. 2024; 52: 101508. doi: 10.1016/j.tsc.2024.101508
7. Shanshan S, Sen G. Empowering learners with AI-generated content for programming learning and computational thinking: The lens of extended effective use theory. Journal of Computer Assisted Learning. 2024; 40(4): 1941-1958. doi: 10.1111/jcal.12996
8. Lin H, Jiang X, Deng X, et al. Comparing AIGC and traditional idea generation methods: Evaluating their impact on creativity in the product design ideation phase. Thinking Skills and Creativity. 2024; 54: 101649. doi: 10.1016/j.tsc.2024.101649
9. He W. AI-Generated Content: From Conception to Communal Engagement. Architectural Design. 2024; 94(3): 110-117. doi: 10.1002/ad.3062
10. Yin H, Zhang Z, Liu Y. The Exploration of Integrating the Midjourney Artificial Intelligence Generated Content Tool into Design Systems to Direct Designers towards Future-Oriented Innovation. Systems. 2023; 11(12): 566. doi: 10.3390/systems11120566
11. Li W. A Study on Factors Influencing Designers' Behavioral Intention in Using AI-Generated Content for Assisted Design: Perceived Anxiety, Perceived Risk, and UTAUT. International Journal of Human–Computer Interaction. 2024; 41(2): 1064-1077. doi: 10.1080/10447318.2024.2310354
12. Gupta P, Mahajan R, Badhera U, et al. Integrating generative AI in management education: A mixed-methods study using social construction of technology theory. The International Journal of Management Education. 2024; 22(3): 101017. doi: 10.1016/j.ijme.2024.101017
13. Smith-Mutegi D, Mamo Y, Kim J, et al. Perceptions of STEM education and artificial intelligence: a Twitter (X) sentiment analysis. International Journal of STEM Education. 2025; 12(1). doi: 10.1186/s40594-025-00527-5
14. Fu X, Brinkley C, Sanchez TW, et al. Text mining public feedback on urban densification plan change in Hamilton, New Zealand. Environment and Planning B: Urban Analytics and City Science. 2024. doi: 10.1177/23998083241272097
15. Tan J. A Critical Research on Xiaohongshu for Information Sharing for Chinese Teenagers. Profesional de la información. 2024; 33(1). doi: 10.3145/epi.2024.0017
16. Fraile-Rojas B, De-Pablos-Heredero C, Mendez-Suarez M. Female perspectives on algorithmic bias: implications for AI researchers and practitioners. Management Decision. 2025. doi: 10.1108/md-04-2024-0884
17. Hosseini E, Taghizadeh Milani K, Sabetnasab MS. Development and maturity of co-word thematic clusters: the field of linked data. Library Hi Tech. 2023; 43(1): 81-113. doi: 10.1108/lht-10-2022-0488
18. Liu D, Zhao Y, Wang G, et al. Thirty Years of Service Failure and Recovery Research: Thematic Development and Future Research Opportunities From a Social Network Perspective. Journal of Service Research. 2023; 27(2): 268-282. doi: 10.1177/10946705231194006

19. Li Y, Lee FL. Social media and the negotiation of travel photo authenticity in the making of Wanghongjingdian in China. Tourist Studies. 2024; 24(3): 221-245. doi: 10.1177/14687976241274807
20. Tao H, Peiying S, Huihui W, et al. How do affective and cognitive involvement affect tourism intentions: a perspective on blogger impact. Current Issues in Tourism. 2024: 1-20. doi: 10.1080/13683500.2024.2392763
21. Chivers BR, Garad RM, Boyle JA, et al. Perinatal Distress During COVID-19: Thematic Analysis of an Online Parenting Forum. Journal of Medical Internet Research. 2020; 22(9): e22002. doi: 10.2196/22002
22. Adeshola I, Adepoju AP. The opportunities and challenges of ChatGPT in education. Interactive Learning Environments. 2023; 32(10): 6159-6172. doi: 10.1080/10494820.2023.2253858
23. Amin SM, El-Gazar HE, Zoromba MA, et al. Sentiment of Nurses Towards Artificial Intelligence and Resistance to Change in Healthcare Organisations: A Mixed-Method Study. Journal of Advanced Nursing. 2024; 81(4): 2087-2098. doi: 10.1111/jan.16435
24. Blazkova T, Pedersen ERG, Andersen KRR. Sentiments and sustainability: stakeholder perceptions of sustainable fashion on social media. Journal of Fashion Marketing and Management: An International Journal. 2025; 29(4): 585-604. doi: 10.1108/jfmm-05-2024-0184
25. Chen J, Shi Y, Yi C, et al. Generative-AI-Driven Human Digital Twin in IoT Healthcare: A Comprehensive Survey. IEEE Internet of Things Journal. 2024; 11(21): 34749-34773. doi: 10.1109/jiot.2024.3421918
26. Chen J, Yi C, Du H, et al. A Revolution of Personalized Healthcare: Enabling Human Digital Twin With Mobile AIGC. IEEE Network. 2024; 38(6): 234-242. doi: 10.1109/mnet.2024.3366560
27. Chen J, Shi Y. Generative AI over Mobile Networks for Human Digital Twin in Human-Centric Applications: A Comprehensive Survey. 2024. doi: 10.36227/techrxiv.172349525.50239637/v2