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Beyond Sentiment: Exploring the Dynamics of AIGC-Generated Sports Content and User Engagement on Xiaohongshu

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Abstract

This study explores the impact of AIGC-generated sports content on user sentiment and engagement on Xiaohongshu, a Chinese social media platform.Using MediaCrawler, we collected posts and comments related to sports topics generated by AI. Sentiment analysis was performed using SnowNLP to classify comments as positive or negative, with 57.1% showing positive sentiment and 42.9% negative. Despite the prevalence of positive sentiment, no significant difference in engagement (measured by likes) was observed between positive and negative comments.Temporal analysis revealed that user engagement is event-driven, with spikes in positive sentiment during major sports events. Additionally, word cloud analysis highlighted promotional and spam-like themes, suggesting challenges in content moderation. The interaction patterns showed a skewed distribution, with a small number of highly active users dominating discussions.The findings suggest that timing, relevance, and event alignment are more critical than sentiment polarity in driving engagement.The study provides insights for content creators and platforms on optimizing AIGC strategies through trend alignment and effective user collaboration.

1. Introduction

In recent years, Artificial Intelligence-Generated Content (AIGC) has emerged as a transformative force within social media and online communities. AIGC encompasses content that is either created or significantly shaped by AI technologies, including text, images, and multimedia. Its ability to generate personalized, relevant content at scale has made it increasingly prominent across industries such as marketing, entertainment, and sports. As user engagement with AIGC grows, understanding its impact on user sentiment, engagement, and interaction patterns becomes essential for platforms and content creators striving to optimize content delivery and promote meaningful interactions(Cao et al., 2023).

This study examines AIGC-generated sports content on Xiaohongshu (Little Red Book), a leading lifestyle-focused social media platform in China. Xiaohongshu is renowned for its dynamic user community, where individuals share content spanning fashion, beauty, travel, fitness, and sports. As the platform integrates AI-generated content into these discussions, it becomes crucial to explore users' emotional responses and how such content shapes engagement behaviors, including likes, comments, and interactions.

The primary aim of this research is to investigate the emotional responses and behavioral patterns linked to AIGC-generated sports content on Xiaohongshu. Specifically, the study assesses whether users predominantly express positive or negative emotions toward AI-generated sports content, how sentiment influences engagement levels, and whether interactions with AIGC content follow temporal patterns or trends. By addressing these questions, the study seeks to provide insights into how AIGC can enhance user experience and foster deeper engagement in online sports discussions(Chen et al., 2024).

While AIGC presents significant opportunities for personalized content creation, challenges remain, including maintaining content quality, relevance, and user satisfaction. User responses to AIGC-generated content may vary based on several factors, such as the timeliness of the content, alignment with user interests, and external events or sports activities(Fan, 2024). Furthermore, AIGC content can attract irrelevant interactions or spam-like behavior, complicating efforts to cultivate meaningful discussions. This research aims to uncover these dynamics through a detailed sentiment analysis of user comments and by tracking engagement patterns over time(Feng, Fong, Guo, & Tan, 2024).

To achieve these objectives, the study adopts a mixed-methods approach, combining sentiment analysis, statistical techniques, and data visualization. Data were collected through web scraping tools, focusing on posts and comments related to sports content, particularly AIGC-driven discussions, on Xiaohongshu. The analysis includes binarized sentiment classification, comparisons of engagement metrics by sentiment category, and time-series analysis to capture fluctuations in sentiment over time. The findings provide actionable insights for platform managers and content creators, helping them better understand how AIGC shapes user behavior and sentiment within the Xiaohongshu community.

This research offers two key contributions. First, it delivers a comprehensive analysis of user sentiment and engagement in the context of AIGC sports content, presenting empirical evidence of how AI-generated content influences online discussions. Second, it identifies both the opportunities and challenges associated with AIGC, offering recommendations for enhancing content delivery and sustaining user interaction. These insights can assist social media platforms and content creators in developing more effective strategies for leveraging AIGC, particularly in sports-related topics(Hu et al., 2023).

The subsequent sections of this paper detail the methodology used to collect, preprocess, and analyze the data, followed by the presentation of the results. The discussion section interprets the findings, acknowledges limitations, and provides practical recommendations for platforms and content creators. Finally, the conclusion highlights the study's key takeaways and suggests future research directions to optimize the use of AIGC in online communities(Lin & Shen, 2023).

2. Methodology and Procedures

This section outlines the methods employed to collect, process, analyze, and visualize data for the study of AIGC-generated sports content on Xiaohongshu. To explore user sentiment, engagement patterns, and interaction dynamics, the research follows a structured and systematic approach. Data collection focused on retrieving relevant posts and comments that reflect user interactions with AIGC content, followed by preprocessing steps to ensure high data quality. Sentiment analysis was performed to assess the emotional tone of user comments, while visualization techniques and statistical methods were applied to extract meaningful insights from the data(Sun & Ly, 2023).

The methodology ensures that the analysis is accurate, reliable, and ethically sound throughout the research process. By utilizing specialized web scraping tools and Chinese-language sentiment analysis libraries, this study captures the nuances of user interactions with AI-generated content and provides a comprehensive view of behavior and engagement dynamics on the Xiaohongshu platform. The following sections offer a detailed explanation of the steps involved in data collection, preprocessing, sentiment analysis, and visualization. This approach equips the study to generate insights into the influence of AIGC content on emotional responses, user interactions, and platform engagement(Tan, 2024).

2.1 Data Collection

The data for this study were collected from Xiaohongshu (Little Red Book), a popular Chinese social media platform known for its community-driven lifestyle content. The focus of this research is on AIGC (AI-Generated Content) related to sports, examining user sentiment and engagement around these topics(Tao, Gao, & Yuan, 2023).

To collect the relevant data, MediaCrawler, a specialized web scraping tool, was employed. This tool enables efficient extraction of public data from social media platforms, ensuring high-quality data retrieval for analysis.

The scraping process was designed to specifically capture posts and comments related to sports topics generated or influenced by AIGC. The process consisted of the following steps:

(1) Identifying AIGC-related Sports Content:

- Keywords were used to filter posts that reference both sports themes (e.g., football, basketball, fitness) and AI-related terms (e.g., AIGC, AI content, generated text).
- Posts that were explicitly tagged or associated with AIGC-generated sports-related discussions were prioritized to ensure the dataset focused on the interaction between AI-generated content and user engagement.

(2) Post Metadata Extraction:

- Post ID: A unique identifier for the post.
- User ID: An anonymized identifier representing the author of the post.
- Post Date: The date and time when the post was published.
- Number of Likes: The total likes received by the post, used as an indicator of user engagement.

(3) Comments Extraction:

- Comment ID: A unique identifier for each comment.
- Post ID: The ID of the post to which the comment is linked.
- User ID: An anonymized identifier of the commenter.
- Comment Content: The text of the comment, used for sentiment analysis.

- Timestamp: The exact time when the comment was made.

The scraping process resulted in two structured datasets. The Post-sport.csv dataset contains sports-related posts generated or influenced by AIGC. It includes fields such as post IDs, user IDs, publication dates, and like counts, which provide the foundation for user engagement analysis. By examining the number of likes and other metadata, this dataset helps explore how users interact with AIGC-generated content on sports topics. The Comments-sport.csv dataset stores comments on these AIGC-related sports posts, with fields such as comment IDs, post IDs, user IDs, comment timestamps, and the comment text. The comments serve as the primary input for sentiment analysis, enabling an understanding of users' emotional responses toward AIGC sports content. The link between posts and their respective comments offers insights into the evolution of discussions and the alignment of sentiment with user interactions.

The data collection process adhered to strict ethical guidelines to ensure responsible use of data from Xiaohongshu. Only publicly accessible posts and comments were scraped, avoiding any private or restricted content, which ensured compliance with privacy and platform regulations. User identifiers, such as user IDs, were anonymized throughout the analysis to protect individual privacy and prevent the exposure of personally identifiable information. The entire data scraping process was conducted in alignment with Xiaohongshu's terms of service to ensure responsible and lawful use of the platform's data. Careful measures were taken to avoid excessive scraping or any actions that could disrupt the platform's normal operations.

By focusing on AIGC-related sports content, these datasets provide a comprehensive foundation for analyzing user sentiment, engagement patterns, and interaction dynamics within the Xiaohongshu community. This targeted data collection ensures that the study captures the interplay between AI-generated content and sports discussions, offering meaningful insights into how AIGC influences user behavior on the platform.

2.2 Preprocessing

The preprocessing step ensures that the data is clean, well-structured, and ready for analysis. Several operations were applied to the datasets to enhance data quality. First, text cleaning was performed on the comments to remove punctuation, special symbols, emojis, and URLs — common elements in social media text that do not contribute meaningfully to sentiment analysis. Non-Chinese characters were also filtered out since the sentiment analysis focused exclusively on Chinese-language content. This step ensured that the textual data was free from noise and optimized for accurate analysis(Wen et al., 2024).

Handling missing values was another crucial part of the preprocessing process. Comments with missing or empty text were removed to maintain data consistency and enable meaningful sentiment evaluation. Additionally, posts without any associated comments were excluded, as they did not provide value for analyzing sentiment trends or engagement metrics. The two datasets — Post-sport.csv and Comments-sport.csv — were merged using post IDs to link each comment to its corresponding post. This integration facilitated a more detailed analysis by associating user engagement metrics, such as likes, with sentiment trends(Xu et al., 2024).

The sentiment analysis tool, SnowNLP, generated sentiment scores ranging from 0 to 1 for each comment. To simplify the analysis, these scores were binarized: comments scoring 0.5 or above were classified as positive, while those scoring below 0.5 were labeled as negative. This binary classification enabled clear comparisons of engagement patterns based on sentiment. Additionally, timestamps for posts and comments were standardized into a consistent datetime format, allowing for the tracking of temporal trends in sentiment over time(Yu, 2025).

To further ensure data quality, duplicate posts and comments were identified and removed to prevent bias or overrepresentation in the results. These preprocessing steps prepared the datasets for accurate sentiment analysis and reliable exploration of engagement patterns. Through careful cleaning, integration, and formatting, the data was optimized for subsequent statistical analysis and visual exploration, laying a strong foundation for meaningful insights(Zhang & Hu, 2024).

2.3 Sentiment Analysis

Sentiment analysis was performed to assess the emotional polarity of user comments on AIGC-generated sports-related posts. This process aimed to classify the sentiment embedded in user interactions and explore how different sentiments correlate with user engagement. The SnowNLP library, specifically designed for Chinese text processing, was utilized to generate sentiment scores.

SnowNLP assigns each comment a sentiment score ranging from 0 to 1, with scores closer to 1 indicating positive sentiment and those closer to 0 representing negative sentiment. To facilitate analysis and enable clearer comparisons, these scores were binarized: comments with scores ≥ 0.5 were labeled as positive, while those scoring < 0.5 were categorized as negative. This binary classification allowed the study to examine how the emotional tone of comments influences user engagement metrics, such as the number of likes on posts(Zhang, Zeng, Xia, Wang, Li, & Cai, 2023).

Once the sentiment scores were assigned and classified, various visual and statistical analyses were conducted. The distribution of positive and negative comments was visualized to understand the general emotional landscape of AIGC-related sports discussions. This analysis aimed to determine whether users predominantly express positive or negative emotions toward AIGC-generated content. A comparison of average likes per sentiment category was also performed to evaluate whether posts with positive comments receive more engagement than those with negative ones.

Additionally, time-series analysis was employed to explore temporal trends in user sentiment. By plotting the frequency of positive and negative comments over time, patterns such as bursts of positive sentiment following major events or shifts in engagement trends were identified. A word cloud visualization was also generated using the text from positive and negative comments, highlighting the most frequently used words in each sentiment category. This provided insights into the themes and topics users emphasize when expressing specific emotions toward AIGC-generated content.

The sentiment analysis uncovered meaningful insights into the emotional dynamics of sports discussions driven by AIGC. It also laid the groundwork for further exploration of how different sentiment types influence user behavior and engagement on Xiaohongshu. However, some limitations of the sentiment analysis are acknowledged. While SnowNLP is effective for general sentiment classification, it may struggle to accurately interpret ironic, sarcastic, or highly nuanced expressions. These limitations are discussed further in the study’s discussion section. Nonetheless, sentiment analysis plays a crucial role in this study, offering valuable insights into how AIGC-related content shapes emotional tone and engagement patterns within Xiaohongshu's sports community.

2.4 Visualization and Statistical Methods

To gain meaningful insights from the sentiment analysis and engagement data, several visualization techniques and statistical methods were employed. These approaches helped uncover patterns, trends, and relationships between user sentiment and engagement metrics in AIGC-related sports content.

The distribution of sentiments (positive and negative) was visualized using pie charts to provide a clear overview of the emotional polarity within the dataset. This visualization allowed for a quick assessment of whether users expressed predominantly positive or negative emotions toward AIGC sports content. Additionally, bar charts were used to compare the average number of likes across posts with different sentiment categories. This analysis aimed to explore whether posts with predominantly positive comments received higher engagement than those with negative comments.

To analyze the temporal dynamics of sentiment, time-series plots were created to track the evolution of positive and negative comments over time. These plots helped identify patterns, such as bursts of positive sentiment following major sports events or trends in engagement linked to specific seasons or campaigns. Understanding these temporal trends provided insights into how user sentiment fluctuates in response to AIGC-related content.

A word cloud was generated using the text from both positive and negative comments, highlighting the most frequently used words. This visualization offered insights into the themes and topics users focus on when expressing different emotions. Word clouds helped reveal key terms, trends, and user preferences in AIGC-generated sports discussions, contributing to a better understanding of the content that resonates with users emotionally.

To explore interaction patterns among users, a weighted degree distribution analysis was performed. This method helped assess the level of user engagement by measuring how frequently users interacted with posts or other users. A histogram of weighted degree distribution was used to visualize the frequency of high-interaction users, providing insights into the dynamics of user interactions within the platform.

Statistical tests were also applied to validate findings. T-tests were conducted to determine whether the difference in the average number of likes between posts with positive and negative comments was statistically significant. Additionally, correlation analysis was performed to examine the relationship between sentiment and engagement metrics, such as likes and comment counts. These statistical methods ensured that the observed patterns and trends were not the result of random variation but reflected meaningful relationships in the data.

Through the combination of visualizations and statistical methods, the study provided a comprehensive understanding of how user sentiment and engagement are influenced by AIGC-generated sports content on Xiaohongshu. These approaches allowed for deeper insights into the dynamics of emotional responses, engagement behavior, and interaction patterns, forming the basis for meaningful interpretations in the discussion section.

3. Results and Discussion

3.1 Results

This section presents the key findings from the analysis of user sentiment, engagement patterns, interaction dynamics, and trends in AIGC-related sports content on Xiaohongshu. Through sentiment analysis, visualizations, and statistical methods, we aim to understand how user emotions and behaviors are influenced by AI-generated content and how these dynamics evolve over time. The results also provide valuable insights for content creators and platforms to strategically engage with users by leveraging trends, events, and key users.

3.1.1 Sentiment Distribution

The sentiment analysis of comments on AIGC-related sports content reveals a predominance of positive sentiment. As shown in the pie chart below, 57.1% of the comments were classified as positive, while 42.9% were negative. This distribution suggests that users, on average, express more favorable emotions toward AIGC-generated content, though a significant proportion of negative sentiment also exists.

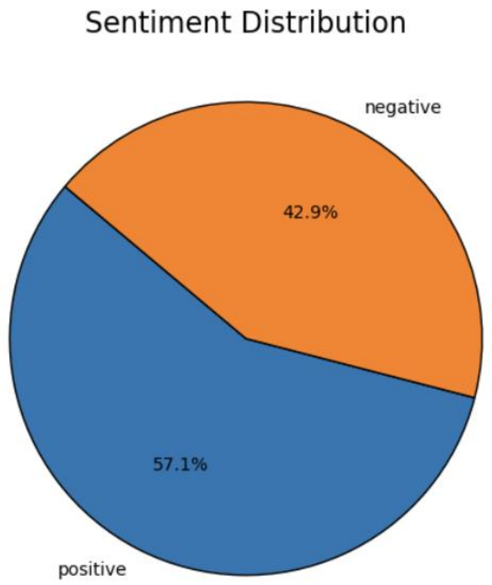

Figure 3.1 Sentiment Distribution Pie Chart

The dominance of positive sentiment reflects an overall positive reception of the AIGC content related to sports topics on Xiaohongshu. However, the substantial presence of negative comments indicates that some users may have reservations or criticisms, possibly due to concerns about content quality, relevance, or other issues.

This distribution provides a foundation for further analysis of how user sentiment impacts engagement, such as the number of likes on posts, and how sentiment trends evolve over time. Understanding this balance between positive and negative emotions is essential for content creators aiming to enhance user satisfaction and engagement through AIGC content.

3.1.2 User Engagement and Sentiment

The relationship between user sentiment and engagement was explored by analyzing the average number of likes on posts with positive and negative comments. As shown in the bar chart, the results reveal no significant difference between the average likes for posts associated with positive comments (approximately 8 likes) and those with negative comments (also around 8 likes).

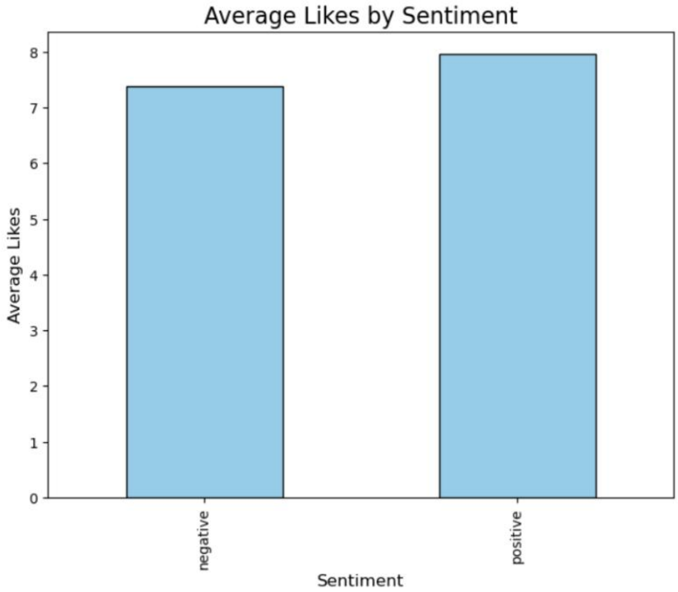

Figure 3.2 Bar Chart - Average Likes by Sentiment

This finding suggests that, for AIGC-generated sports content on Xiaohongshu, user sentiment may not directly influence engagement as measured by the number of likes. Both positive and negative posts appear to receive a similar level of engagement, indicating that users may interact with content regardless of its emotional tone.

These results offer valuable insights for content creators and platform managers, suggesting that the emotional polarity of user sentiment may not always determine the popularity or reach of AIGC content. Instead, factors such as relevance, timing, or topic of the content might play a more important role in driving user interaction. This finding contrasts with the common assumption that positive sentiment leads to higher engagement and highlights the complexity of user behavior in online communities.

3.1.3 Temporal Trends in Sentiment

The time-series analysis of positive comments reveals significant fluctuations over time, as illustrated in the figure below. The distribution shows a sharp initial peak in mid-2022, with more than 600 positive comments recorded within a short period. This likely corresponds to a major sports event or a campaign where users actively engaged with AIGC-generated sports content. However, after this early surge, the number of positive comments dropped substantially and remained relatively low for an extended period.

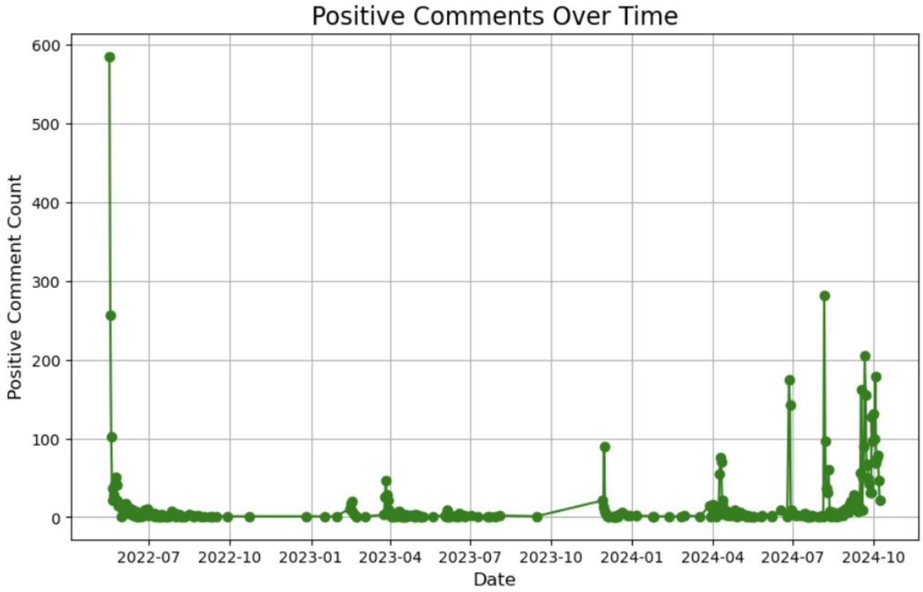

Figure 3.3 Time Series Plot - Positive Comments over Time

The graph also highlights several smaller peaks in positive sentiment during mid-2024, with noticeable increases in engagement around specific months. These smaller spikes suggest that certain events or sports activities may have triggered renewed interest and prompted users to engage positively with AIGC-related content. The increased frequency of smaller peaks toward the end of the time frame suggests that user engagement with AIGC sports content has been gaining momentum recently.

The visualization indicates that user sentiment tends to be event-driven, with positive emotions peaking around key activities or trending topics. The long periods of low activity between peaks suggest that consistent engagement with AIGC sports content remains a challenge. These findings highlight the importance of aligning AIGC content with sports calendars or major events to maximize positive sentiment and engagement over time.

3.1.4 Topic Themes from Word Cloud Analysis

The word cloud visualization provides insights into the key themes and topics present in the comments on AIGC-related sports content. As shown in the figure below, certain keywords appear prominently, indicating the central focus of user discussions. Words like “接中一等奖” (winning the first prize), “巨款” (huge amount of money), and “永久有效” (permanently effective) are frequent, suggesting that a significant portion of user comments may be influenced by lottery or prize-related topics. This pattern could indicate the presence of promotional or spam-like interactions in the discussions, possibly impacting the quality of engagement with the content.

The word cloud also reflects user enthusiasm and engagement with the platform, as terms like “大乐透” (lottery) and “七星彩” (Seven-Star Lottery) are common. While these words may not align directly with traditional sports-related themes, they reveal that AIGC-related content might have attracted discussions beyond conventional sports topics, indicating broader user interest or opportunistic usage of the comment space.

Figure 3.4 Word Cloud of Comments

This word cloud highlights the most frequently occurring words in the comments, offering a snapshot of user discussions and the themes that dominate interactions on AIGC-generated sports content.

The presence of promotional and lottery-related language suggests that content moderation strategies may be necessary to maintain the quality of user discussions. Furthermore, the divergence from purely sports-related topics could reflect the challenges of managing user-generated content in online communities. These findings provide valuable insights into the dynamics of AIGC-related engagement and emphasize the importance of monitoring and curating discussions to ensure meaningful interaction.

3.1.5 Interaction Patterns and Weighted Degree Distribution

The distribution of weighted degrees provides insights into the interaction patterns among users engaging with AIGC-generated sports content. As shown in the histogram below, the distribution is highly skewed, indicating that a small number of users account for a disproportionate amount of interaction, while the majority of users participate at a much lower frequency.

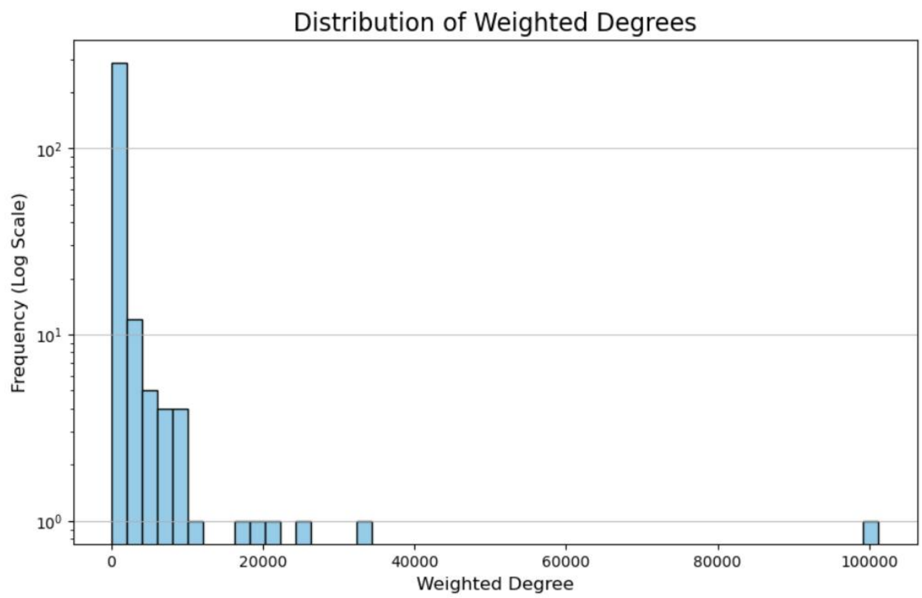

Figure 3.5 Distribution of Weighted Degrees

The logarithmic scale used on the vertical axis emphasizes the sharp decline in frequency as the weighted degree increases. A large portion of users exhibit low interaction levels, with only a handful of users contributing significantly to the discussions, possibly acting as key influencers or community leaders. The presence of outliers, such as a few users with weighted degrees reaching 100,000, suggests that a select group of individuals are highly active, driving much of the engagement and interaction on the platform.

This pattern aligns with typical online community dynamics, where the majority of users engage sporadically, while a small group of power users dominate interactions. The uneven interaction pattern reflected in the weighted degree distribution suggests that platform managers and content creators could benefit from identifying and collaborating with these highly active users to sustain engagement and promote discussions around AIGC content.

These findings emphasize the importance of targeting influential users and monitoring interaction dynamics to maintain healthy and engaging discussions within online communities.

3.1.6 Trend of AIGC-Related Posts' Likes

The trend of total likes on AIGC-related sports posts reveals a clear fluctuation in user engagement over time, as shown in the figure below. The trend begins with a steady increase from mid-2023, reaching a peak of over 6,000 likes in early 2024. This rapid rise in engagement suggests that user interest in AIGC sports content grew significantly during this period, possibly driven by major sports events or trending topics that aligned with the AI-generated content.

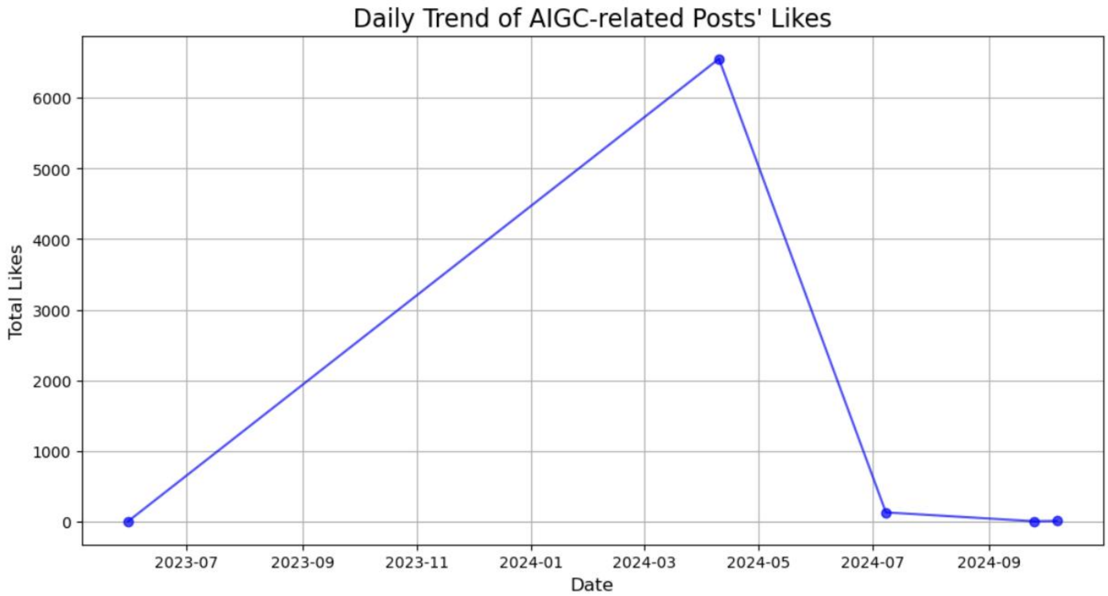

Figure 3.6 Daily Trend of AIGC-Related Posts' Likes

However, following the peak, there is a sharp decline in the number of likes, dropping to near-zero levels by mid-2024. This drop-off indicates a potential decrease in user interest or engagement with AIGC-related content, highlighting the ephemeral nature of engagement on social media platforms. The low engagement levels observed toward the end of the timeline may also suggest that the content failed to maintain user attention or align with current trends during that period.

These results emphasize the importance of timing and relevance in driving engagement for AIGC-generated sports content. Platforms and content creators can leverage these insights by synchronizing content delivery with major sports events or actively monitoring trends to sustain user interaction. The findings highlight the need to continuously adapt AIGC content to the changing interests of the audience to maximize engagement over time.

3.1.7 Summary of Key Findings

The results of this study provide a comprehensive understanding of how AIGC-generated sports content influences user sentiment, engagement, and interaction patterns on Xiaohongshu. The key findings can be summarized as follows:

(1) Sentiment Distribution:The sentiment analysis revealed that 57.1% of the comments were classified as positive, while 42.9% were negative. This indicates a generally favorable user response to AIGC-generated content, though negative sentiment remains substantial, reflecting some level of user dissatisfaction or criticism.

(2) User Engagement and Sentiment:The comparison of average likes across posts showed that there was no significant difference in engagement between posts with positive and negative comments. Both sentiment categories had similar average likes, indicating that sentiment polarity alone may not be a key driver of user engagement with AIGC sports content.

(3) Temporal Trends in Sentiment:The time-series analysis of positive comments revealed spikes in sentiment during major sports events, demonstrating that user emotions are event-driven. However, the analysis also identified periods of low engagement, suggesting that maintaining consistent user interest requires timely and relevant content.

(4) Topic Themes from Word Cloud Analysis:The word cloud visualization highlighted unexpected themes in user comments, including lottery-related terms such as "一等奖" (first prize) and "巨款" (huge sum). This finding indicates that non-sports-related content or spam-like interactions may impact the quality of discussions surrounding AIGC sports content.

(5) Interaction Patterns and Weighted Degree Distribution:The analysis of interaction patterns showed a highly skewed weighted degree distribution, with a small number of highly active users driving most interactions. This suggests that engagement is concentrated among a few key users or influencers, while the majority of users participate at a lower frequency.

(6) Trend of AIGC-Related Posts' Likes:The engagement trend for AIGC-related posts peaked in early 2024, followed by a sharp decline. This suggests that user interest in AIGC content is short-lived and that maintaining engagement requires continuous alignment with current trends and events.

In summary, these findings underscore the importance of timing, relevance, and strategic content creation for sustaining engagement with AIGC-generated sports content. Although user sentiment is generally positive, engagement appears to be influenced more by external events and key users rather than emotional polarity alone. To maximize the potential of AIGC content, platforms and content creators must monitor trends closely, identify influential users, and align content delivery with major events to sustain user interest and participation.

3.2 Discussion

The findings of this study offer valuable insights into how AIGC-generated sports content shapes user sentiment, engagement, and interaction patterns on Xiaohongshu. Sentiment analysis revealed a predominance of positive sentiment, with 57.1% of comments classified as positive and 42.9% as negative. This indicates that users generally respond favorably to AIGC-generated content. However, the significant proportion of negative comments suggests that some users may harbor reservations, potentially related to concerns about content relevance, authenticity, or quality. This balance between positive and negative sentiment underscores the importance of aligning content with user expectations to sustain favorable engagement.

An analysis of average likes across posts with positive and negative comments found no significant difference between the two groups, challenging the assumption that positive sentiment alone drives engagement. This suggests that other factors—such as content relevance, timing, and alignment with trending topics—play a more critical role in influencing user interactions. The findings highlight the complexity of user behavior, where emotional polarity is not always the decisive factor in engagement. Instead, users may interact with content for other reasons, such as novelty, entertainment value, or connections to broader events.

The temporal analysis of positive comments demonstrated that engagement is often event-driven. Significant spikes in positive sentiment coincided with major sports events or activities, reflecting the impact of external events on shaping user interactions. However, periods of low engagement were also observed, indicating that maintaining consistent interaction with AIGC content remains a challenge. This highlights the need for platforms and content creators to align their strategies with the sports calendar and leverage trending events to optimize engagement.

The word cloud analysis revealed unexpected themes in user comments, with frequent references to lottery-related terms such as "一等奖" (first prize) and "巨款" (huge amount). These findings suggest that promotional or spam-like interactions may influence the nature of discussions around AIGC sports content, raising concerns about content quality. This underscores the importance of implementing effective moderation strategies to filter out irrelevant or disruptive comments and foster meaningful engagement within the community.

The analysis of user interaction patterns through weighted degree distribution revealed that engagement is highly skewed, with a small number of active users driving most interactions. This pattern aligns with typical online community dynamics, where a few key influencers or power users play a crucial role in sustaining discussions. However, reliance on a small group of users raises concerns about the sustainability of engagement. If these key contributors lose interest, overall interaction levels may decline. Identifying and supporting these influencers, while encouraging broader participation, can help platforms sustain long-term engagement.

A trend analysis of likes on AIGC-related posts showed a sharp increase in engagement during early 2024, followed by a steep decline. This pattern reflects the short-lived nature of engagement on social media platforms and the need for continuous adaptation to evolving trends and user interests. Platforms and content creators must actively monitor trends and align content delivery with major events to sustain interaction. These results suggest that engagement with AIGC content depends heavily on timeliness and relevance, further emphasizing the importance of trend alignment.

While this study offers meaningful insights, several limitations should be acknowledged. The use of SnowNLP for sentiment analysis may not fully capture nuanced expressions, such as sarcasm or humor, potentially affecting sentiment classification accuracy. Additionally, the binary classification of sentiment into positive and negative categories may overlook mixed or neutral emotions, limiting the depth of the analysis. Keyword-based filtering to identify AIGC-related content may have introduced bias by including irrelevant posts or excluding relevant ones, particularly in the word cloud analysis, where promotional content was unexpectedly prominent. Furthermore, since this study focuses solely on Xiaohongshu, the findings may not be generalizable to other social media platforms with different user demographics and behaviors.

These findings highlight the complex dynamics of AIGC-generated content and its interaction with user behavior on Xiaohongshu. Although positive sentiment is prevalent, engagement depends more on relevance, timing, and key influencers than emotional polarity alone. Platforms and content creators must continuously adapt their strategies to maintain alignment with user interests and current events. Collaborative efforts with influencers, effective content moderation, and timely, relevant content delivery will be essential to sustaining long-term engagement with AIGC-generated sports content.

4. Conclusion and Suggestion

The findings of this study provide valuable insights into how AIGC-generated sports content influences user sentiment, engagement, and interaction patterns on Xiaohongshu. Sentiment analysis revealed a predominance of positive sentiment, with 57.1% of comments classified as positive and 42.9% as negative. This indicates that users generally respond favorably to AIGC-generated content. However, the significant proportion of negative comments suggests that some users may have reservations, possibly due to concerns about the relevance, authenticity, or quality of the content. This balance between positive and negative sentiment highlights the importance of aligning content with user expectations to sustain favorable engagement.

An analysis of average likes across posts with positive and negative comments found no significant difference between the two groups, challenging the assumption that positive sentiment alone drives engagement. This suggests that other factors—such as content relevance, timing, and alignment with trending topics—play a more critical role in influencing user interactions. These findings highlight the complexity of user behavior, where emotional polarity is not always the decisive factor in engagement. Instead, users may engage with content for other reasons, such as novelty, entertainment value, or connections to broader events.

The temporal analysis of positive comments demonstrated that engagement is often event-driven. Significant spikes in positive sentiment coincided with major sports events or activities, reflecting the impact of external events on shaping user interactions. However, periods of low engagement were also observed, indicating that maintaining consistent interaction with AIGC content remains a challenge. This emphasizes the need for platforms and content creators to align their strategies with the sports calendar and leverage trending events to optimize engagement.

The word cloud analysis uncovered unexpected themes in user comments, with frequent references to lottery-related terms such as "一等奖" (first prize) and "巨款" (huge amount). These findings suggest that promotional or spam-like interactions may affect the nature of discussions around AIGC sports content, raising concerns about content quality. This underscores the importance of implementing effective moderation strategies to filter out irrelevant or disruptive comments and foster meaningful engagement within the community.

The analysis of user interaction patterns through weighted degree distribution revealed that engagement is highly skewed, with a small number of active users driving most interactions. This pattern aligns with typical online community dynamics, where a few key influencers or power users play a crucial role in sustaining discussions. However, reliance on a small group of users raises concerns about the sustainability of engagement. If these key contributors lose interest, overall interaction levels may decline. Identifying and supporting these influencers, while encouraging broader participation, can help platforms sustain long-term engagement.

A trend analysis of likes on AIGC-related posts showed a sharp increase in engagement during early 2024, followed by a steep decline. This pattern reflects the transient nature of engagement on social media platforms and the need for continuous adaptation to evolving trends and user interests. Platforms and content creators must actively monitor trends and align content delivery with major events to sustain interaction. These findings suggest that engagement with AIGC content depends heavily on timeliness and relevance, further emphasizing the importance of trend

alignment.
While this study offers meaningful insights, several limitations should be acknowledged. The use of SnowNLP for sentiment analysis may not fully capture nuanced expressions, such as sarcasm or humor, potentially affecting sentiment classification accuracy. Additionally, the binary classification of sentiment into positive and negative categories may overlook mixed or neutral emotions, limiting the depth of the analysis. Keyword-based filtering to identify AIGC-related content may have introduced bias by including irrelevant posts or excluding relevant ones, particularly in the word cloud analysis, where promotional content was unexpectedly prominent. Furthermore, as this study focuses solely on Xiaohongshu, the findings may not be generalizable to other social media platforms with different user demographics and behaviors.
These findings highlight the complex dynamics of AIGC-generated content and its interaction with user behavior on Xiaohongshu. Although positive sentiment is prevalent, engagement depends more on relevance, timing, and key influencers than emotional polarity alone. Platforms and content creators must continuously adapt their strategies to maintain alignment with user interests and current events. Collaborative efforts with influencers, effective content moderation, and timely, relevant content delivery will be essential for sustaining long-term engagement with AIGC-generated sports content.

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