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Original Paper

What Drives Deep Reader Engagement with Socially-Generated Content? The Critical Role of Dual-Layer Information

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Abstract
Social media platforms have rapidly gained popularity due to features such as personalized recommendations and real-time push notifications, attracting a large number of creators to produce content. However, with the explosive growth of content and information overload, readers' expectations for content and interaction quality have increased, making it increasingly difficult to engage them deeply. This poses management challenges to the platform's ecosystem, such as high visitor volume but low retention rates. This study, leveraging the latest GPT technology, provides a more scientific approach to content metrics and a detailed exploration of interaction categories to examine the impact of information, authors, and interactions on reader engagement behavior. It particularly considers the effects of internal and external layers of social-generated content and different levels of reader engagement. Combining real community data, it is found that the impact of content information is the most crucial, with this impact being distributed across content and interaction aspects. It is suggested that social media platforms should strive to balance vivacity and informativeness when producing content. Additionally, the role of content, authors, and interactions varies across different product categories, so differentiated strategies should be employed accordingly.
Keywords
Internal and external layers of information, Interaction quality, Content creator, Social media platforms, Social-generated content, Reader Engagement

1. Introduction

With the maturation of internet technologies, the characteristics of social media platforms, such as personalized recommendations, social interaction, and instant notifications, have attracted a large number of creators (Pletikosa et al., 2013). Creators enhance their influence by managing Facebook pages (Luarn et al., 2015), WeChat public accounts (Y. et al., 2019) or publishing content on other social media platforms. According to reports, Xiaohongshu has over 20 million monthly active creators, with an average daily publication of over 3 million posts. This phenomenon signifies that socially-generated content is gradually becoming an important content creation trend (Rishika et al., 2019), and the 26.5 billion interactions generated by these posts further demonstrate readers' active participation in this content creation ecosystem.

However, despite the rapid growth of socially-generated content and the large readership it attracts, not all social media content effectively stimulates online reader engagement (Braojos et al., 2019). Studies on reader engagement behavior suggest that such behavior is mainly driven by structural factors, informational factors, and social factors (Stafford et al., 2008). Social factors, such as the credibility and influence of the creator, significantly impact online reader engagement (Jin et al., 2014). However, with the explosive growth of content and the overflow of information, readers have higher demands for information quality (Davis et al., 2020) and interaction quality (Sohn & Kim, 2020). Therefore, this paper aims to investigate the impact of socially-generated content's information quality (inner and outer layers), creator quality, and interaction quality on reader engagement behavior through more scientific content quality indicators and more detailed interaction categories.

At the same time, the evolution of social media platforms has also changed the interaction methods between readers and between customers and businesses (Trunfio et al., 2021), leading to a diversification of user engagement behaviors. This shift has moved from the early stage of one-way browsing to various forms including sharing and forwarding, posting original content, and participating in live broadcasts. The growth rate of new engagement behaviors is significantly higher than that of traditional behaviors, with the growth rate of sharing and forwarding being particularly notable. The change in the depth of engagement behaviors has had a significant impact on reader stickiness and content dissemination on platforms (艾瑞咨询, 2020). Therefore, we propose the second research question: (2) How do information quality, creator quality, and interaction quality affect different reader engagement behaviors?

In order to answer the above two questions, this paper proposes a reader engagement model for social media content containing content, social and interactive quality based on the information adoption and service dominance model and obtains 74,327 real data from the largest social media content platform in China, and analyzes them in depth using the latest GPT technology. Due to the unique information flow pattern of social media platforms, the information quality is split into inner and outer layers to explore the different impacts of these two layers of factors on readers' behavioral engagement, in order to provide more specific guidance for the content; secondly, unlike the previous interactive perspective (Zhuang et al., 2023), this paper takes the interactive content as the main perspective and refines the information interaction and friendship interaction to make up for the limitations of previous studies; at the same time, through the analysis of the main body of the content comments. At the same time, through the analysis of the subject of content comments, this paper subdivided the participation behavior into in-role and out-of-role behaviors; finally, combining the content categories of real social media platforms (including lifestyle, beauty and technology) as moderating variables, this paper studied the differences in the performance of different social media content, in order to reveal the key factors of the content in the interaction and information delivery, so as to help platforms optimize content strategies, enhance communication effects and improve reader participation. The study provides a more comprehensive perspective and empirical support for social media content optimization.

2. Literature Review and Theoretical Background

2.1 Social-generated Content

Scholars tend to agree on the definition of UGC, which is different from the media-led content generation mode, but refers to the self-created content published by users on social media platforms (Michael et al., 2018). In the new era of technological development, content dissemination has gradually shifted from "mass" to "social", and the main body of creation has gradually shifted from the media to the users, and more and more people are acquiring information through social media platforms, and UGC is therefore widely spread, playing an important role in the contact between enterprises and customers play an important role in contacting with customers (Rishika et al., 2013). Sorting out the relevant studies on user-generated content, it can be found that for social media winning content mainly focuses on popularity (Goh et al., 2013) and purchase desire (Angela et al., 2018), such as positive brand-related UGC will stimulate consumers' eWOM behaviors, which will increase consumers' brand engagement and with potential brand sales. However, relatively few studies have been conducted on how it affects readers' engagement behavior, often ignoring the complexity and diversity of content and readers, and this study aims to fill this gap by delving into the full impact of UGC content on readers' engagement behavior to provide a more nuanced analysis.

2.2 Reader Engagement

Previously, scholars defined customer participation as "the level of expression of individual mental states" (Brodie et al., 2011), but now scholars have defined more practical participation behaviors in the online environment, such as browsing, interacting, and creating behaviors (Malthouse et al., 2013), in which Yi and Gong scholars divided user participation behaviors into in-role and out-of-role behaviors based on the service-dominant theory. It is believed that in-role behaviors are the behaviors that are necessary for users to achieve participation; while out-of-role behaviors refer to those that are not explicitly required, including the three dimensions of feedback, recommendation, and help (Gong et al., 2013). Combined with the specific behaviors such as browsing and interacting that readers show in UGC communities, this paper divides behaviors into in-role and out-of-role with reference to the theory of value co-creation. Past scholars have empirically demonstrated that social motivation is an important influence on readers' participation behavior (Kangas et al., 2018), while information motivation has received little attention from scholars, this paper hopes to focus on information, social and interactive research to comprehensively study the influence brought to readers' participation behavior, and expects to explore the upper and lower bounds of the three different values to provide a more comprehensive explanation of users' participation behavior.

2.3 Information Adoption Model (IAM) and Research Model Development

The Information Adoption Model (IAM) proposed by Sussman & Siegal (2003), which considers information quality and source credibility as two key attributes of online content, with information quality referring to the credibility of the content and source credibility to the reliability of the content's source (Lis et al., 2013), provides a powerful explanation of the processes and factors involved in readers' decision-making about content adoption in the age of computer-mediated communication, and has been widely used to explain "how users process and adopt information in online environments" as these two characteristics help readers to focus only on useful and relevant information to make quick decisions within a short period of time. It can help readers focus only on useful and relevant information and make decisions in a short period of time (Erkan et al., 2016), so the theory has been widely used to explain "how users process and adopt information in online environments" (Zhao et al., 2020), and for social media platforms, these two elements are especially critical, so the IAM as a theoretical model seems to be particularly appropriate.

Based on the IAM theory, past studies have contributed a great deal of wisdom in the field of electronic word-of-mouth; however, in the field of reader engagement behavior research, although some scholars have also pointed out that authorial professionalism and popularity (Breves et al., 2019) and content readability and emotional intensity (Han et al., 2020) can have an impact on content quality and thus change reader engagement behavior, no scholars have yet explored whether the hierarchical content quality of socially-generated content as well as the quality of interactions can affect readers' engagement behaviors, nor have they delineated readers' engagement behaviors. In this paper, we will focus on the two elements of information quality and content source, especially incorporating the quality of interaction, which is a unique feature of social media platforms, to identify the quality of socially-generated content from three dimensions and formulate a research model as shown in **Figure 1**, to explore how they affect readers' different engagement behaviors on social media platforms.

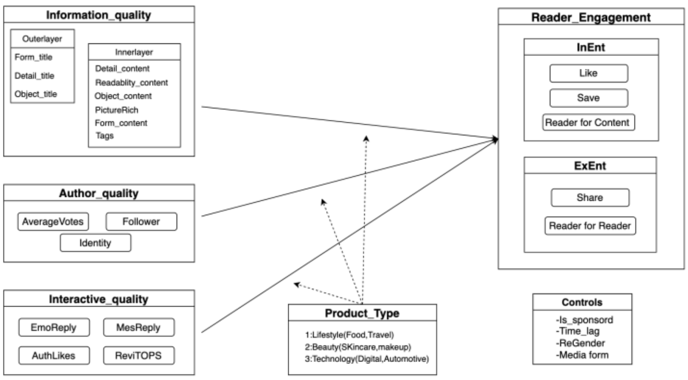

Figure 1. Research Model

3. Hypotheses Development

3.1 Internal and External Layers of Information

The value of the information provided by the UGC community can be in the form of information searches resulting from keywords in a section of the content or an explanation of the functionality of a product. Dessart states that in the online environment information quality is defined as "the user's perception of the quality of the information presented on a website and reflects a comparison between the user's expectations and perceptions of the information disseminated (2015), and when users perceive the information as rich and useful, they may feel obliged to reward the readers of the post through the act of replying (Yang, 2013). Accordingly, the following hypotheses are proposed:

> $H1_a$: Information quality has a positive effect on reader engagement behavior and is significantly higher for out-of-character stimuli than in-character behavior.

UGC content is generally presented in two parts, as shown in **Figure 2**, readers cannot see the post until they click on the post, and can only view it after clicking on the cover of the post, and it is only during this reading stage that the inner features of the post are presented (Tan et al., 2021), and this approach leads to a lack of rich information in the outer layer, which needs to be repeatedly stimulated and persuaded by the content features to produce repetition and spacing effects (Toppino et al., 2014), according to which it can be judged that the outer layer features of the post mainly affect in-role behaviors such as the number of reads, while the stimulation of sharing and readers to help with out-of-role behaviors is relatively small relatively small, corresponding to the hypothesis:

$H1_b$: Inner and outer layer information has positive influence on reader engagement behavior, and inner layer information has higher influence on reader engagement.

$H1_c$: Outer layer information is significantly less stimulating to reader out-of-role behaviors than in-role behaviors.

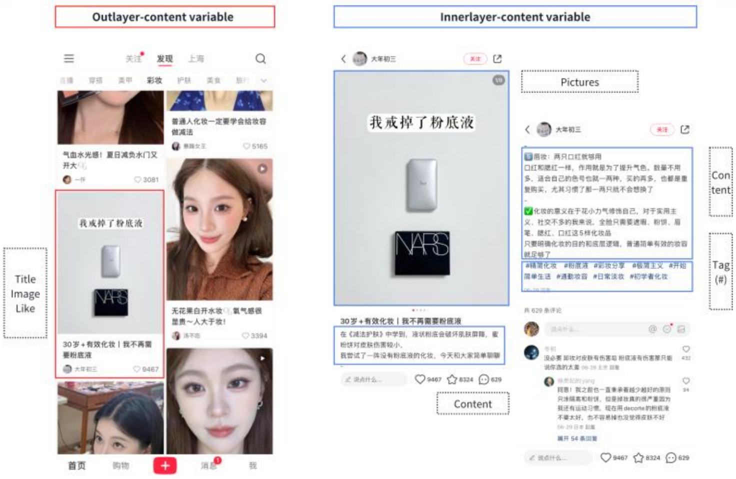

Figure 2. Internal and External Layers of Information

3.1.1 External Layers of Information

The outer information generally refers to the content attractiveness brought by the cover and title of socially generated content (Chen et al., 2020) such as the language, language style and picture style of music cover titles have strong positive correlation with the number of times the music is played and commented on (Davis et al., 2020); strategic titles and the degree of investment show positive correlation, and positively emphasized titles are more likely to receive investment. In social media platforms, covers and captions are the primary elements for accurately and effectively conveying content information and attracting readers' interest. Due to the limitations of graphical analysis techniques, this paper will use the three dimensions of caption language vividness, degree of detail, and objectivity to assess the quality of outer layer information. Accordingly, the following hypotheses are proposed:

H2a: The richness of the headline's linguistic form has a positive effect on reader engagement.

H2b: The objectivity of headlines has a positive effect on reader engagement behavior.

Similarly, in the field of UGC. Silvia (2018) studying travel products, found that users usually spend a lot of time and effort in choosing a travel route, and that the impact of headlines in online travel is much higher than in other categories (Silvia et al., 2013). Consumers prefer concise and simplified communication of information elements and judge the reliability and relevance of that UGC content from the headline.

H2c: Headline detail has a positive effect on reader engagement behavior.

H2d: Headline length has a positive effect on reader engagement behavior.

3.1.2 Internal Layers of Information

Inner layer information generally refers to the repeated stimulation of readers through the body of socially generated content with additional features to increase content credibility and appeal (Toppino et al., 2014). Earlier studies have shown that the use of images, videos, and sounds to describe products can increase content vividness and comprehension (Jiang et al., 2007), and different forms of content presentation will bring different attractions to readers, for example, vehicles such as videos with sound and image descriptions are more likely to stimulate engagement behaviors such as liking, sharing, and commenting. Therefore, the hypothesis is proposed:

H3a: Pictures have a stronger role in positively influencing readers' engagement behaviors than videos among content presentation formats.

In the field of e-commerce, it has been found that sales posts with direct information clues about products or services are more conducive to stimulating user engagement behaviors (Yap et al., 2013), and in the same comparison to social media platforms, post length usually reflects the amount of information provided by the post, and the more words a post contains, the greater the probability that it conveys more information (Filieri, 2015). Through the post length affects the information content and thus the user's engagement behavior, and high-quality UGC tends to attract more users (Fang et al., 2018). Accordingly, we propose the following hypothesis:

H3b: Content detail has a positive effect on reader engagement behavior.

H3c: Image richness has a positive effect on reader engagement behavior.

H3d: The number of topic tags has a positive effect on reader engagement behavior.

Previous research in the Zhihu high-quality content eco-community has also found that content readability and objectivity have a positive effect on liking and sharing (Davis et al., 2014), content readability is defined as the ease with which the information presented in a post can be accepted by the reader, and complex posts require more cognitive effort to decode the information and re-comprehend it, and redundant content may prevent readers from quickly accessing useful information, thus making it difficult to engage consumers in any behavior. Redundant content may prevent readers from obtaining useful information quickly, thus making it difficult to attract consumers to engage in any behavior (Kim et al., 2017). Content objectivity refers to objectively stated opinions and unbiased representations, and excessive emotional judgments may cause consumers to question the authenticity of the content (Zhang et al., 2018), in which indirectly affects their active participation behavior (Yang, 2013). Same in social media platforms, we propose the following hypothesis:

H3e: Content readability has a positive effect on reader engagement behavior.

H3f: Content objectivity has a positive effect on reader engagement behavior.

3.2 Content Creator

Due to the unprecedented scalability and dissemination speed of social media platforms, the author's influence has been a key element influencing readers' engagement behaviors (Katz et al., 1995), with numerous studies emphasizing the content creator's personal qualities such as the number of followers and the number of posts (Jin et al., 2014). Social media platforms typically display cumulative reader feedback (i.e., likes or favorites) for content on the creator's homepage, representing the total amount of content the creator has published in the past that has been recognized by members of the community (Dong et al., 2021), and other scholars in the field of eWOM have found that positive tweets from Instagram celebrities with many followers influence consumers' willingness to purchase and generate more effective reviews (Jin et al., 2014). In addition, in social media platforms there are usually identifiers to represent the core characteristics and social recognition of an individual to be able to differentiate from others (Ichikawa et al., 2005), which is considered particularly important to build trust and credibility for the creator's audience (Lee et al., 2021), therefore, in the context of social media platforms, the popularity, recognition, and identifiers of a creator to some extent represent the quality of the creator's personality. Accordingly, we have found that the popularity, recognition and identifiers of a creator in the social media platform environment represent the quality of the creator's personality, i.e., the credibility of the content, and therefore, the quality of the content source credibility, accordingly, we propose the following hypothesis:

H4: Author quality has a positive effect on reader engagement behavior and is higher for in-character stimulation than for in-character behavior.

H4a: Social acceptance has a positive effect on reader engagement behavior.

H4b: Social popularity has a positive effect on reader engagement behavior.

H4c: Identity has a positive effect on reader engagement behavior.

3.3 Interaction Quality

Previous studies have pointed out that on social media platforms, content creators' interaction with users (Li & Huang, 2020; Xue et al., 2020) can promote users' engagement with their content, but as the types of interactions are gradually diversifying, which are reflected in the creators' responses to readers' interactions such as commenting, liking, and other interactive behaviors (Zhuang et al., 2023), and social media platforms generally identify the authors' liking and top commenting, according to this. Accordingly, we judge that "author's likes and top comments are a favorable way to stimulate readers' engagement behavior". In addition, when the creator interacts more with readers online, he may provide comments to supplement and explain the statements in the UGC, thus increasing readers' trust in the quality of the content (Yang et al., 2021); or he may show friendliness and cordiality to the readers, reducing the sense of distance between him and the readers, thus increasing readers' trust in the content. Through the above measures, readers tend to be more likely to engage in engaging behaviors with the content, and similarly, the more information content the creator provides during the interaction, the more likely it is that readers will engage to a deeper level of feedback (Jin et al., 2014). Accordingly, we propose the following hypothesis:

H5: Interaction quality has a positive effect on reader engagement behavior, and is lower for in-character stimuli than for in-character behavior.

H5a: High emotional response counts will have a positive effect on reader engagement behavior.

H5b: High number of informative responses will have a positive effect on reader engagement.

H5c: Author liking rate and comment topping rate will have a positive effect on reader.

H5d: A high number of message responses will have a positive effect on readers' deeper engagement behavior.

3.4 Moderating Effects of Content Categories

Given the realistic content categories, we categorize UGC content into lifestyle, beauty and technology. Different categories of content may cause different impacts on users, e.g., promotional content attracts more shares, UGC content that introduces new products but receives fewer likes (Schultz, 2017), and entertainment posts do not have a significant impact on customer out-of-character engagement (Devries et al., 2012). In this study, we wish to drop the above hypotheses into actual content categories, investigate the different impacts brought by the above values, and extend the current requirements for

UGC features in different categories of China's most popular UGC community, Xiaohongshu. Therefore, the following hypotheses are proposed:

H6a: Content type moderates the impact of the above values on user engagement behavior.

H6b: The impact of information value on reader engagement will be amplified for technology and digital products; the impact of interactive and social values will be amplified for beauty products.

4. Research Methodology

4.1 Data Collection

To verify the above hypotheses, this paper selects Xiaohongshu as the data sampling platform in which the monthly active users have exceeded 100 million, the annual note release volume reaches 300 million, the daily note exposure of more than 10 billion times, having become the world's largest UGC community. The station UGC presents the distribution of the real-life category, as the most appropriate research platform.

Based on the content recommendation mechanism of Xiaohongshu, we will use a brand-new account to crawl 1,000 pieces of UGC content (6,000 pieces in total) from June 2023 to February 2024 using Python algorithm according to the six channels of food, travel, skincare, makeup, digital and automotive, and eliminate the notes that have 100,000 and 100,000 likes and comments and whose titles are not empty. In order to ensure that the exposure time of each UGC tends to be more or less the same, after excluding the UGC that was released 60 days before the data collection, the comment content is uniform and the number of fans is very small, there are 2392 representative note contents left, and in order to better control the number of notes of different product contents, 350 randomly selected notes from each channel among the 2392 notes (A total of 2100 notes) as a sampling sample.

4.2 Variables and Measurement

4.2.1 Dependent Variables

Based on Yi and Gong scholars' definition of engagement behaviors (Yi & Gong, 2013), this paper classifies UGC reader engagement on social media platforms into in-role and out-of-role types, with in-role simple engagement behaviors and out-of-role representing higher-level engagement behaviors, which in Xiaohongshu are specifically represented by the three basic in-role behaviors of liking, bookmarking, and readers' commenting on the work, and the definition of sharing and readers' replying to readers as Higher level of participation in the role of extra behavior. Likes, favorites and shares can be obtained directly from the original web page data, while the data of readers commenting on works and readers replying to readers need to be obtained by comparing the creator ID, the original posting ID of the comment and the comment reply ID, and the obtained data corresponds to the original web page data as shown in **Figure 3**.

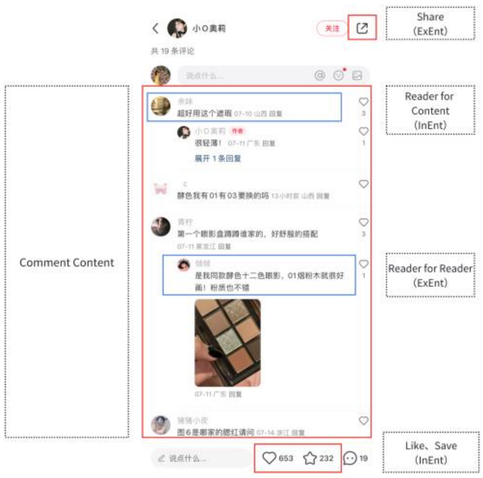

Figure 3. Dependent Variables

4.2.2 Content-related Independent Variables

Existing studies more often use the length of the text to measure the level of detail of the content (Choi et al., 2020), in this paper, we will explain and define the content quality of the inner and outer features separately, the outer information will measure the headline linguistic form (Tan et al., 2021), the length and the information content; the inner information will be the inner quality through the level of detail, objectivity, readability, images, expression, the number of topic labels Algorithmic statistics.

The level of detail in the content will be assessed through text analysis techniques by counting the number of words related to the post's information. Posts are typically connected to the content conveyed by the channel and title, which helps determine the relevance of the post. To evaluate the information content more effectively, the LDA model is first used to determine the topic of each post. Next, the JieBa model performs lexical processing on the post's content and after eliminating irrelevant lexemes, the lexical similarity is calculated using Tencent's pre-trained Chinese word vector library. This process helps compute the number of effective keywords in the content, the number of effective keywords related to the channel's topic, and the number of related to the post's topic. Finally, the number of effective keywords related to the post's topic is calculated with a 2:3:5 weighting.

To obtain indicators of content objectivity, we refer to the methods used by previous scholars to analyze sentiment words in UGC text by identifying and extracting them. After extracting the posts, the text needs to be preprocessed. This preprocessing involves extracting sentiment features, eliminating irrelevant non-text information, transforming expressions into text information, and performing case transformation. Finally, nouns, adjectives, verbs, and adverbs are identified, and the content sentiment polarity and sentiment value, ranging from -1 to 1, are analyzed using TextBlob and BERT models.

As for content readability, due to the Chinese text currently lacks specific indicators to measure readability. Most scholars tend to use text length to represent information readability, and the fewer the words tend to take the shorter the time of effort (Gupta, 2010). Based on the above judgment, this paper will use the ratio of total content length to total number of sentences to assess the readability of content.

4.2.3 Variables Related to Creators and Interaction

We will use social recognition, social popularity (Zhuang et al., 2023), and identity (Jin et al., 2014) markers to reflect the social influence and quality of the post authors. Social recognition refers to the total number of likes and saves that a creator's historical content has received on the Xiaohongshu content platform; this data is directly displayed on the creator's personal profile. Additionally, the number of followers on the creator's personal profile is defined as social popularity. Identity markers, as a measure of professionalism, must be obtained through text collection techniques related to the channel's identity markers.

This paper's interactive content only includes feedback content centered on the author. Typically, on community comment pages, author replies are marked with an "author" label. We sample these reply data and use the GPT model to simultaneously input the article's topic and contextual dialogue to determine the sentiment of the author's current replies. Sentiment values range from -1 to 1; replies with values above 0.5 or below -0.5 are categorized as high sentiment replies. Similarly, the information content of sampled data is averaged, and comments above the average line are classified as high information replies. Finally, we collect "author likes" and "pinned" comment content, calculate the proportions of liked comments and pinned comments among all comments, corresponding to the metrics of author like rate and comment pin rate.

4.2.4 Moderating Variables

According to past research, users have different content requirements for technology-oriented and experience-oriented products (Chua et al., 2016). The former typically demands higher information quality, while the latter is often more influenced by the social impact of the blogger, leading to more emotional responses such as likes or shares (Zhao et al., 2020). This paper uses product type as a moderating variable and examines its impact on readers' perceptions of information, authors, and interactions, considering the actual product categories in the community (makeup, skincare, automobiles, digital products, travel, and food).

4.2.5 Control Variables

To mitigate the effect of other elements on the reliability of the results, such as the time of exposure of the post, the gender of the readers, and the sponsorship of the advertisements. It is known that the longer the post is exposed, the more probability it must be read and the more chance it has to get likes, so the time interval between content release and data collection needs to be considered. In addition, since advertising content in the Xiaohongshu community is often identified in the outer layer, advertising will increase reader aversion and thus reduce the probability of users clicking on it, so whether the advertisement sponsored content is also controlled in this paper.

Based on the above analysis, the definitions, and measurements of the final variables in this study are shown in **Table 1**.

Table 1. Variable Definitions

Category	Variables	Code	Description and Measurement
Dependent Variables			
Engagement	InRole-Engagement	InEnt	The total number of likes, saves, and comments on the content from readers.
	OutRole-Engagement	ExEnt	The total number of shares and responses by readers to other readers.
Independent variable			
InformationQ	Title Format	$Form_{Title}$	Categorical variable indicating the format of the title. 0: Text-only, 1: Emojis-only, 2: Both text and emojis.
	Title Detail	$Detail_{Title}$	The amount of information included in the title.
	Title Objectivity	$Objvity_{Title}$	The emotional value of the title, on a scale from 0 (completely objective) to 1 (highly emotional).
	Title Length	$Length_{Title}$	The length of the title in terms of words.
	Content Detail	$Detail_{Content}$	The number of key information keywords related to the product extracted from the UGC.
	Content Readability	$Read_{Content}$	The average length of sentences, calculated as the total length of content divided by the number of sentences.
	Content Objectivity	$Object_{Content}$	The average emotional value of the content.
	Picture Richness	PictRich	The total number of images in the UGC post.
	Content Format	$Form_{Content}$	A categorical variable indicating the format of the content. 0: video text, 1: photo text.
	Tags	Tag_{Number}	The number of thematic tags (indicated by “#”).
SocialQ	Social	$Average_{Votes}$	The average number of “likes” and “saves”

	Recognition		received by all UGC posts from the creator.
	Social Popularity	Follower	The total number of followers of the creator.
	Identity Identification	Identity	A categorical variable indicating whether the creator has identity identification. 0: no,1: yes.
InteracteQ	HighEmotion Replies	$Replies_{Emo}$	The count of comments from the author that have an emotional value higher than 0.5.
	HighInformation Replies	$Replies_{Mes}$	The count of sentences in the author's replies that contain high information content.
	AuthorLikeS	AuthLikes	The ratio of the number of likes given to comments by the author to the total number of comments.
	CommentPin Rate	ReviTops	The ratio of the number of comments pinned by the author to the total number of comments.
Moderating Variable			
Product Type		PdType	Categorical variable indicating the type of product. (1/2/3).
Control Variables			
Time Interval		Time_lag	Days of UGC post has been exposed.
ReaderGender		ReGender	The ratio of male to female users who comment on the UGC post.
Sponsored or not		Is_sponsored	Whether the UGC is sponsored by a brand. 1=yes, 0=no.

5. Empirical Results and Analysis

5.1 Descriptive Statistics

Through a series of data preprocessing and text analysis, 1,800 samples were finally obtained, and the descriptive statistical results of each variable were output using STATA, as shown in **Table 2**. The table shows that the standard deviations of the strain variable and the social value index are higher, while the data range for other indexes is mostly within 0-200, with small differences in data peaks.

Table 2. Descriptive Statistics

Variables	Minimum	Maximum	Mean	Standard Deviation	Median
In Engagement	250.000	72767.000	2927.591	3762.697	1844.500
Extra Engagement	0.000	13719.000	197.831	618.525	43.000
Form Title	0.000	2.000	0.573	0.903	0.000
Length Title	1.000	36.000	15.776	5.364	17.000
Detail Title	0.000	9.000	4.591	1.943	5.000
Objectivity Title	-1.000	1.000	0.770	0.307	0.800
Detail Content	0.000	20.000	15.531	6.057	20.000
Readability Content	2.000	131.000	13.137	8.838	10.423
Follower	6.873	7283.649	2352.165	5259.329	934.596
Average Votes	1.000	86074.000	31664.427	2937.482	15832.000
Objectivity Content	-1.000	1.000	0.537	0.703	0.800
Picture Richness	1.000	18.000	4.105	4.169	1.000
Identity	0.000	1.000	0.584	0.493	1.000
Form Content	1.000	2.000	1.541	0.498	2.000
Tag_Number	0.000	43.000	6.786	5.121	6.000
Emotional Replies	0.000	190.000	5.600	13.597	2.000
Message Replies	0.000	188.000	2.512	8.365	1.000
Author Likes	0.000	1.000	0.021	0.069	0.000
Review Tops	0.000	0.200	0.004	0.015	0.000
Product Type	1.000	3.000	2.333	0.730	2.000
Reader Gender	0.000	1.000	0.541	0.399	0.429

To avoid high correlation between independent variables, Person correlation coefficient as well as VIF values of each variable were calculated, and the results are shown in **Table 3**, the variable correlation coefficients did not appear to be higher than 0.5, and the VIFs were all less than 1.5, which indicates that the data do not have obvious covariance problems.

Table 3. Results of Correlation Analysis

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1																	
2	0.164**	1																
3	0.094**	0.069**	1															
4	0.069**	0.075**	-0.002	1														
5	0.028	-0.014	-0.030	-0.035	1													
6	0.024	0.006	0.038	0.021	0.022	1												
7	-0.09**	-0.08**	-0.14**	-0.030	0.001	-0.050*	1											
8	0.37	0.031	0.024	0.034	-0.034	0.050*	-0.040	1										
9	-0.043	0.037	-0.12**	-0.011	-0.010	-0.039	0.314**	-0.009	1									
10	0.000	-0.009	0.016	0.016	-0.016	0.145**	-0.055*	0.053*	-0.020	1								
11	0.066**	0.082**	0.034	0.061**	-0.012	0.031	-0.08**	0.050*	-0.07**	0.073**	1							
12	0.059*	0.054*	0.027	-0.008	0.011	-0.022	-0.052*	0.015	-0.010	0.005	0.039	1						

13	0.083**	0.051*	0.046	0.059*	0.026	0.064**	-0.011	0.056*	0.011	0.055*	0.072**	0.018	1					
14	0.042	0.041	0.057*	0.027	-0.013	0.036	-0.08**	0.054*	-0.07**	0.043	0.048*	0.050*	0.031	1				
15	0.104**	0.020	0.036	0.064**	0.019	0.020	-0.07**	0.047*	-0.024	-0.002	0.055*	0.053*	0.058*	0.031	1			
16	0.069**	0.077**	0.072**	0.060*	-0.004	0.001	-0.020	0.036	-0.024	0.033	0.102**	0.021	0.073**	0.136**	0.019	1		
17	0.029	0.028	0.020	0.054*	0.023	-0.001	-0.028	0.080**	-0.034	0.009	0.050*	0.011	0.024	0.018	0.042	0.010	1	
18	0.198**	0.233**	0.272**	0.140**	0.001	0.107**	-0.49**	0.115**	-0.33**	0.120**	0.192**	0.022	0.194**	0.161**	0.122**	0.151**	0.084**	1

5.2.1 Master Models

Based on the primary research question, the following model containing control variables or not was constructed based on the theory, and the regression results are shown in **Table 4**:

(1) Constructing the effects of informational, social, and interaction quality on in-role/out-of-role behavior:

$$InEnt = \alpha_{11} + \beta_{11} Inform_Q + \beta_{12} \mathrm{Social}_Q + \beta_{13} \mathrm{Interactive}_Q + \eta_{11} Controls + \varepsilon_{11} \quad (1\text{-}1)$$

$$ExEnt = \alpha_{21} + \beta_{21} Inform_Q + \beta_{22} \mathrm{Social}_Q + \beta_{23} \mathrm{Interactive}_Q + \eta_{21} Controls + \varepsilon_{21} \quad (1\text{-}2)$$

Table 4. The Dependent Variable Is the Regression Model for Within-Role/Outside-Role Behaviors

	Model 1 (InE)		Model 2 (ExE)	
Constant	389.209 (1.054)	167.614 (0.371)	-435.331** (-8.325)	-317.289** (-4.978)
$\mathrm{Interactive}_Q$	202.816** (11.874)	202.157** (11.822)	66.749** (27.592)	67.100** (27.781)
Social_Q	0.010** (8.909)	0.010** (8.913)	0.001** (7.045)	0.001** (7.045)
Inform_Q	290.859** (8.973)	292.273** (8.900)	73.051** (5.060)	72.297** (5.082)

Time_lag		7.597 (0.854)		-4.047** (-3.222)
N	1800	1800	1800	1800
adjusted R^2	0.138	0.138	0.360	0.363
F	F (3,1796)=96.799,p=0.000	F (4,1795)=72.770,p=0.000	F (3,1796)=338.224,p=0.000	F (4,1795)=257.588,p=0.000

It was evident that all three types of quality showed positively correlated significant effects in the two engagement behaviors (p<0.01), and the standardized coefficient of information quality was higher in Model 2, then H4 and H5 held. However, the coefficient of information quality stimulating in-role behaviors was higher, so $_{\text{H1a}}$ partially held, and it was evident that information, in facilitating deeper out-of-role behaviors of a person, would be more likely to trigger shallow in-role behaviors, stimulating readers to more positively to respond to posts with more behaviors (Davis et al., 2014).

(2) In order to explore the influence of each element of information, author, and interaction value on readers' engagement behaviors, separate models were developed as follows：

$$\begin{aligned} InEnt = {} & \alpha_{21} + \beta_{21}Form_{\mathrm{t}} + \beta_{22}Detail_{\mathrm{t}} + \beta_{23}\mathrm{Objectivity}_{\mathrm{t}} + \beta_{24}Length_{\mathrm{t}} + \beta_{25}Detail_{\mathrm{c}} \\ & + \beta_{26}\mathrm{Readability}_{\mathrm{c}} + \beta_{27}\mathrm{Objectivity}_{\mathrm{c}} + \beta_{28}\mathrm{PictureRich} + \beta_{29}Form_{c} \\ & + \beta_{20}Tags + \gamma_{21}\mathrm{Votes} + \gamma_{22}\mathrm{Followers} + \gamma_{23}\mathrm{Identity} + \delta_{11}\mathrm{EmReplies} \\ & + \delta_{12}\mathrm{MeReplies} + \delta_{13}\mathrm{AuLikes} + \delta_{14}\mathrm{ReviewTops} + \eta_{21}Controls + \varepsilon_{21} \end{aligned} \quad \text{(1-3)}$$

$$\begin{aligned} InEnt = {} & \alpha_{31} + \beta_{31}Form_{\mathrm{t}} + \beta_{32}Detail_{\mathrm{t}} + \beta_{33}\mathrm{Objectivity}_{\mathrm{t}} + \beta_{34}Length_{\mathrm{t}} + \beta_{35}Detail_{c} \\ & + \beta_{36}\mathrm{Readability}_{c} + \beta_{37}\mathrm{Objectivity}_{c} + \beta_{38}\mathrm{PictureRich} + \beta_{39}Form_{c} \\ & + \beta_{30}\mathrm{Tags} + \gamma_{31}\mathrm{Votes} + \gamma_{32}\mathrm{Followers} + \gamma_{33}\mathrm{Identity} + \delta_{31}\mathrm{EmReplies} \\ & + \delta_{32}\mathrm{MeReplies} + \delta_{33}\mathrm{AuLikes} + \delta_{34}\mathrm{ReviewTops} + \eta_{31}Controls + \varepsilon_{31} \end{aligned} \quad \text{(1-4)}$$

The regression results are shown in **Table 5**. In the main model (Model 3) for within-role behaviors, it can be seen that the richness of outer layer information titles (t=4.5; p<0.01) and detail (t=2.3; p<0.05) both show a positive correlation, supporting hypotheses H2a and H2c. The detail of inner layer information (t=2.3; p<0.05), image richness (t=2.3; p<0.05), number of tags (t=7.6; p<0.01), and readability (t=2.3; p<0.05) also show positive correlations, supporting hypotheses H3b, H3c, H3d, and H3e. Comparing the contribution rates of inner and outer layer information, the impact of inner layer information is significantly higher than that of outer layer information, supporting hypothesis H1b. Further observation of the significance of author and interaction factors reveals that all elements of author quality show positive correlations, and the contribution coefficients to within-role behaviors are significantly higher than those for outside-role behaviors, supporting hypotheses H4, H4a, H4b, H4c, and H4d. Regarding interaction quality, high-emotion replies (t=4.0; p<0.01) and like-comment rates (t=2.9; p<0.05) show positive correlations with within-role behaviors, but the number of high-information replies does not fully correlate positively, showing a positive correlation with within-role behaviors but a lower correlation with outside-role behaviors, supporting hypotheses H5a, H5b, and H5c.

Table 5. The Full-factor Regression Model for Within-role/outside-role Behaviors

	Model 3 (InE)			Model 4 (ExE)	
Constant	3578.435** (10.658)	3629.897** (9.758)	Constant	-178.054** (-3.873)	-122.155* (-2.402)
Follower	0.042** (4.244)	0.042** (4.249)	Follower	0.006** (4.196)	0.006** (4.257)
Average Votes	0.002** (8.529)	0.002** (8.523)	Average Votes	0.000** (6.320)	0.000** (6.302)
Identity	894.864** (8.576)	895.597** (8.579)	Identity	34.782* (2.434)	35.579* (2.493)
Form Title	255.594** (4.502)	255.445** (4.498)	Form Title	51.651** (6.644)	51.490** (6.633)
Length Title	3.319 (0.351)	3.259 (0.345)	Length Title	0.437 (0.338)	0.372 (0.288)
Detail Title	61.988* (2.352)	62.526* (2.367)	Detail Title	-3.443 (-0.954)	-2.859 (-0.792)
Objectivity Title	-3283.538 (-18.657)	-3285.449 (-18.652)	Objectivity Title	-66.489 (-2.759)	-68.565 (-2.848)
Detail Content	25.569** (3.049)	25.439** (3.029)	Detail Content	4.664** (4.061)	4.523** (3.940)
Readability Content	-61.765** (-9.728)	-61.687** (-9.706)	Readability Content	-3.907** (-4.494)	-3.823** (-4.400)
Objectivity Content	260.648** (3.570)	260.526** (3.567)	Objectivity Content	-7.449 (-0.745)	-7.581 (-0.759)
Picture Richness	62.214** (4.927)	62.122** (4.917)	Picture Richness	15.990** (9.246)	15.891** (9.201)
Form Content	-168.252	-168.835	Form Content	51.810**	51.177**

	(-1.655)	(-1.660)		(3.722)	(3.682)
Tag_Number	82.251** (7.625)	82.131** (7.608)	Tag_Number	11.840** (8.015)	11.710** (7.935)
Emotional Replies	15.465* (4.004)	15.563* (4.015)	Emotional Replies	3.541** (6.693)	3.648** (6.885)
Message Replies	28.267* (2.764)	28.253* (2.762)	Message Replies	7.700 (5.498)	7.685 (5.496)
Author Likes	2955.898** (3.921)	2953.451** (3.917)	Author Likes	1455.828** (14.102)	1453.169** (14.097)
Review Tops	8055.718* (2.038)	8120.101* (2.051)	Review Tops	3901.918** (7.208)	3971.851** (7.340)
Time_lag		-1.759 (-0.322)	Time_lag		-1.911* (-2.555)
adjusted R^2	0.431	0.430	adjusted R^2	0.362	0.364
F	$F(17,1760)=80.047$, $p=0.000$	$F(18,1759)=75.567$, $p=0.000$	*F*	$F(17,1760)=60.326$, $p=0.000$	$F(18,1759)=57.517$, $p=0.000$

Note. dependent variable=In Engagement, dependent variable=Extra Engagement, *$p<0.05$ **$p<0.01$ (t-value in parentheses).

5.2.3 Moderating Effects of Content Categories

(3) Moderating variables content categories on the modeling of the effects of informational, social, and interactional quality on engagement behaviors:

$$\begin{aligned} Engagement = \alpha_{51} + \beta_{52} Inform_Q + \beta_{52} Social_Q + \beta_{53} Interactive_Q \\ + \beta_{54} \text{ProductType} \times Inform_Q + \beta_{55} \text{ProductType} \times Social_Q \\ + \beta_{56} \text{ProductType} \times Interactive_Q + \varepsilon_{51} \end{aligned} \quad (1\text{-}5)$$

Table 6. Results of the Moderating Effect of Content Categories

	Model 10			Model 11			Model 12	
Constant	1753.938** (9.247)	1644.357** (8.630)	Constant	1751.765** (9.293)	1981.366** (11.147)	Constant	1840.505** (10.126)	1963.640** (11.242)
Time_lag	4.893 (0.966)	6.239 (1.235)	Time_lag	3.629 (0.721)	1.050 (0.222)	Time_lag	0.095 (0.019)	-4.218 (-0.904)

InformV	302.010** (9.102)	-1.973 (-0.025)	SocialV	0.006** (10.306)	0.038** (11.605)	InterV	147.395** (15.907)	123.092** (4.386)
Type1.0 [refer to]	-	-	Type1.0 [refer to]	-	-	Type1.0 [refer to]	-	-
Type-2.0	-630.607** (-4.372)	-610.056** (-4.206)	Type-2.0	417.038** (-2.943)	-474.648** (-3.535)	Type-2.0	-371.689** (-2.722)	-274.396* (-2.093)
Type-3.0	-213.832 (-1.564)	-136.613 (-0.991)	Type-3.0	-292.236* (-2.148)	-421.357** (-3.276)	Type-3.0	-303.265* (-2.315)	-275.370* (-2.193)
InformV *Type-2.0		421.101** (4.337)	SocialV* Type-2.0		-0.018** (-4.953)	InterV*Type-2.0		209.219** (6.378)
InformV *Type-3.0		324.024** (3.461)	SocialV* Type-3.0		-0.036** (-10.799)	InterV*Type-3.0		-50.686 (-1.677)
N	1800	1800	N	1800	1800	N	1800	1800
adjusted R^2	0.047	0.056	*adj* R^2	0.059	0.171	*adj* R^2	0.126	0.198
F	F (4,179)=23.319,p=0.000	F (6,179)=18.881,p=0.000	F	F (4,179)=29.194,p=0.000	F (6,179)=62.814,p=0.000	F	F (4,179)=66.1,p=0.000	F (6,1793)=75.080,p=0.000

The regression results are shown in **Table 6**. The moderating effect of content categories on information quality with respect to engagement behavior is positive (Int), indicating that the moderator strengthens the positive impact of information on engagement behavior. Specifically, when the product category is the third type (technology and digital products), the positive impact of information value on engagement behavior is stronger. Conversely, for product categories, the social value and interaction value's effect on engagement behavior is negative (Int), suggesting that the moderator weakens the positive impact of author and interaction quality on engagement behavior. Hypotheses H6 and H6a are supported.

5.3 Robustness Test

To test the robustness of the main effects in the study, two methods were employed in **Table 7**: variable substitution and sample grouping. First, regarding variable substitution, all user-related behaviors were included in the engagement behavior for regression analysis, and the total engagement behavior was calculated using the ln method, as shown in Model 13. Second, considering that Xiaohongshu's main users are female and that information transmission thinking among women is similar, female bloggers' posts may more effectively trigger readers' engagement behaviors. Therefore, the sample was divided into two groups based on the gender of UGC bloggers, with a ratio of 2:3, and the results are shown in Models 14 and 15.

Table 7. Robust Regression Results

	Model 13	Model 14(Male)	Model 15(Female)
常数	6.670** (57.181)	1339.478** (3.811)	1582.415** (6.865)
Follower	0.000** (4.658)	0.047** (4.524)	0.014* (2.437)
Average Votes	0.000** (0.588)	0.001* (2.091)	0.002** (5.176)
Identity	0.265** (8.194)	388.546** (4.320)	431.200** (6.530)
Form Title	0.075** (4.282)	174.732** (3.595)	123.164** (3.420)
Length Title	0.009** (2.920)	18.355* (2.081)	6.060 (1.006)
Detail Title	0.056** (6.834)	30.293 (1.247)	41.032* (2.540)
Objectivity Title	-0.747** (-13.655)	-1667.104** (-8.913)	-1528.557** (-14.954)
Detail Content	0.014** (5.123)	22.975** (3.127)	23.209** (4.214)
Readability Content	-0.013** (-5.758)	-19.738** (-3.323)	-18.218** (-3.864)
Objectivity Content	0.158 (7.006)	26.584 (0.412)	225.057 (4.933)
Picture Richness	0.022** (5.447)	56.339** (5.142)	39.384** (4.794)
Form Content	-0.004*	-123.179	-6.810*

	Model 13	Model 14(Male)	Model 15(Female)
	(-0.136)	(-1.362)	(-0.108)
Tag_Number	0.025** (7.361)	59.969** (6.034)	47.883** (7.013)
Emotional Replies	0.230* (0.028)	3.130* (0.590)	0.297* (0.088)
Message Replies	0.073 (0.920)	15.610* (1.910)	4.461 (0.599)
Author Likes	0.443** (1.895)	1999.594** (3.572)	2061.328** (3.682)
Review Tops	1.946** (1.592)	6237.883* (1.837)	5411.950* (2.157)
Time_lag	0.000 (0.058)	1.970 (0.409)	-3.684 (-1.076)
Information Value*ReaderGe	-0.075** (-9.448)	-86.435** (-3.803)	66.092** (3.002)
Interactive Value*Reade	0.035** (2.991)	50.178 (1.225)	-0.004** (-1.829)
Social Value*ReaderGe	0.032** (1.937)	-0.001** (-0.491)	-107.298** (-6.751)
N	1778	656	1122
adjusted R^2	0.426	0.470	0.490
F	$F(21,1756)=63.919, p=0.000$	$F(21,634)=28.674, p=0.000$	$F(21,1100)=52.270, p=0.000$

In summary, the conclusions of the aforementioned grouped regression results are broadly consistent with the conclusions of the main effects, indicating that the findings are relatively robust. However, in cases with a smaller sample size, some variables did not show significant effects.

Table 8. Hypothesis Testing Results

	Hypothesis	Result
Infor-mation quality	$H1_a$: Information quality has a positive effect on reader engagement behavior, and is significantly higher for out-of-character stimuli than in-character behavior.	Partial support
	$H1_b$: Inner layer information has higher influence on reader engagement.	Supported
	$H1_c$: Outer-information is significantly less stimulating to reader out-of-role behaviors than in-role behaviors.	Supported
	$H2_a$: Richness of the title form has a positive effect on reader engagement.	Supported
	$H2_b$: Objectivity of title has a positive effect on reader engagement behavior.	No
	$H2_c$: Title detail has a positive effect on reader engagement behavior.	Supported
	$H2_d$: Title length has a positive effect on reader engagement behavior.	No
	$H3_a$: Pictures have a stronger role in positively influencing readers' engagement behaviors than videos among content presentation formats.	No
	$H3_b$: Content detail has a positive effect on reader engagement behavior.	Supported
	$H3_c$: Image richness has a positive effect on reader engagement behavior.	Supported
	$H3_d$: The number of topic tags has a positive effect on reader engagement behavior.	Supported
	$H3_e$: Content readability has a positive effect on reader engagement behavior.	Supported
	$H3_f$: Content objectivity has a positive effect on reader engagement behavior.	No
Author quality	H4: Author quality has a positive effect on reader engagement behavior and is higher for in-character stimulation than for in-character behavior.	Supported
	$H4_a$: Social acceptance has a positive effect on reader engagement behavior.	Supported
	$H4_b$: Social popularity has a positive effect on reader engagement behavior.	Supported
	$H4_c$: Identity has a positive effect on reader engagement behavior.	Supported
Interaction quality	H5: Interaction quality has a positive effect on reader engagement behavior and is lower for in-character stimuli than for in-character behavior.	Supported
	H5a: High emotional response counts will have a positive effect on reader engagement behavior.	Supported
	H5b: High number of informative responses will have a positive effect on reader engagement behavior.	
	H5c: Author liking rate and comment topping rate will have a positive effect on reader engagement behavior.	No
	H5d: A high number of message responses will have a positive effect on readers' deeper engagement behavior.	Supported

		No
content categories	$H6_a$: Content type moderates the impact of the above values on user engagement behavior.	Supported
	$H6_b$: The impact of information value on reader engagement will be amplified for technology and digital products; the impact of interactive and social values will be amplified for beauty products.	Partial support

6. Discussion and Implications

6.1 Key Findings

This study focuses on "reader engagement behavior", establishing more scientific content quality metrics and detailed interaction categories to explore how social media platforms drive user engagement with social-generated content. It primarily addresses three issues: 1) the impact of internal and external content information, author quality, and interaction quality on reader engagement behavior; 2) whether information quality, author quality, and interaction quality affect different types of reader engagement behavior; 3) the real-world effects of these influences on different product types.

Based on real sample data, firstly, the quality of social-generated content, including information, authors, and interactions, all enhance reader engagement behavior. However, unlike previous studies, the impact coefficient of information quality is the highest, and higher information quality leads to more pronounced out-of-role reader behavior. Secondly, concerning the internal and external information structure of posts, readers prefer titles with high richness and detail. Internal content characteristics such as vividness, readability, image richness, and the number of tags significantly boost reader engagement, with internal information having a significantly greater impact than external information, indicating that users on social media still highly value content information quality. Thirdly, regarding creators' responses, emotional interactions more effectively promote reader engagement, and this interaction is more effective for out-of-role reader behavior. For informational interactions, a positive correlation is observed in posts by male creators but not found in posts by female creators. Fourthly, when these findings are applied to real product categories, it is found that technology-related product posts need to provide more informational value to enhance reader engagement, while lifestyle and beauty-related posts rely more on the creator's popularity, recognition, and identity to generate higher reader engagement.

6.2 Theoretical Implications

This study has four main theoretical contributions: First, based on media richness theory and IAM theory, it further divides readers' engagement behaviors into role-based and non-role-based behaviors, enriching the research perspective on reader engagement with social media-generated content. Second, the study focuses comprehensively on the element of quality, examining the impact of information, author, and interaction quality on reader engagement behavior. Unlike previous research on information quality, this study distinguishes between internal and external layers of information content, exploring the different effects of these layers on reader engagement. Additionally, unlike previous studies on interaction, this study emphasizes interaction quality and categories, using text analysis techniques to separate information and friendship dimensions of interaction, providing a clearer and more in-depth understanding of UGC comment content on social media. By analyzing different types of interactions and cognitive efforts in creator feedback, it enhances the understanding of how different posting strategies drive various engagement behaviors across different product categories.

6.3 Managerial Implications

This study may offer some insights for the governance of social media platforms. Firstly, it is essential to recognize that the quality of content, authorship, and interactions remains a key factor in fostering reader engagement, with information quality being particularly influential in driving deeper engagement. Secondly, platform managers should pay attention not only to titles but also to the content of posts when managing content. Titles should use clear language and concise summaries to boost engagement, while the readability and level of detail in posts should be enhanced. For creators, this can involve considering principles of sentence structure, while for platform managers, providing content templates could help reduce inconsistencies in content editing among creators, thereby improving community quality and the overall level of content creation.

Moreover, platforms should distinguish between friendly interactions and informational interactions, with the latter requiring more vivid product representations to foster deeper engagement. The roles of information, authorship, and interaction quality vary across different product categories. In tech communities, ensuring the value of information should be prioritized due to the more rational thinking of their audience. In lifestyle and food communities, the use of visual elements such as images and emojis can enhance appeal.

6.4 Limitations and Future Directions

Although this paper adopts a scientific empirical research process throughout the study, there are still some limitations:

(1) This paper further breaks down and explores the impact of internal and external information on participation behavior. However, external information can influence internal information, making it difficult to conduct controlled group experiments. Additionally, in the external characteristics, the position of the post (Schultz, 2017) and the cover image are crucial elements. Due to technical reasons, these variables were not considered in this study.

(2) Interaction, as a prominent influencing factor, is highly likely to affect readers' judgment of information quality, indicating a moderating effect between interaction and information. Moreover, interaction is a continuous process, suggesting that the response rate is closely related to the degree of information exchange. Information exchange is more likely to trigger deeper engagement behavior, indicating that knowledge stickiness exists in online communities. Future research could explore the relationship between interaction value and participation behavior based on more precise response frequency data.

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