Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 6, 2400-2423
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i6.8406

The role of customer engagement in enhancing repurchase intention and eWOM through technology-driven experiences: A stimulus-organism-response perspective of Xiaohongshu

Chen Xiaodan[1], Niyom Suwandej[2*]
[1,2]College of Innovation and Management, Suan Sunandha Rajabhat University, Bangkok, Thailand; s64584945034@ssru.ac.th (C.X.) niyom.su@ssru.ac.th (N.S.)

Abstract: This study investigates the role of customer engagement in enhancing repurchase intention and electronic word-of-mouth (eWOM) through technology-driven experiences on Xiaohongshu, using the Stimulus–Organism–Response (S-O-R) model. Drawing on a mixed-methods approach, the study examines how social interaction, information quality, and perceived value (stimuli) influence cognitive, emotional, and behavioral engagement (organism), which in turn affect repurchase intention and eWOM (responses). Quantitative data from 407 Xiaohongshu users in Shanghai and qualitative insights from 17 in-depth interviews reveal that all hypothesized relationships are supported. The findings highlight that platform-driven stimuli significantly shape user engagement and that engagement is a key driver of loyalty and advocacy. The integration of technology, content quality, and user community experience creates a robust foundation for sustained behavioral outcomes. This research contributes to the literature on digital engagement and offers practical insights for optimizing social commerce strategies.

Keywords: *Customer engagement, eWOM, S-O-R model, Repurchase intention, Technology-driven experience.*

1. Introduction

In today's digital economy, customer engagement has emerged as a critical driver of business success, shaping how businesses interact with, retain, and nurture their customer base. As consumers become increasingly connected, informed, and empowered, traditional approaches to customer interaction are no longer sufficient. Businesses must now focus on fostering more profound, meaningful customer relationships to ensure long-term loyalty, advocacy, and sustainable growth [2]. Engagement is no longer purely transactional; it encompasses emotional, cognitive, and behavioral dimensions influencing customer decisions and perceptions at every stage of their journey. Consequently, customer engagement has become integral to modern business strategies, directly influencing profitability, competitive advantage, and brand sustainability [3].

The digital era has revolutionized how businesses and customers interact. Social media platforms, e-commerce websites, mobile applications, and online forums provide businesses with unparalleled opportunities to connect with their audiences. These platforms allow for real-time communication, personalized interactions, and the ability to address customer needs quickly and precisely [4]. For instance, customers can voice concerns via a tweet or a review, and businesses can respond almost instantly, demonstrating attentiveness and care. Such direct and immediate interaction fosters stronger relationships and builds trust. However, this increased connectivity also brings challenges. Customers now have heightened expectations for responsiveness, authenticity, and personalization. A single negative experience can be amplified across digital networks, potentially damaging a brand's reputation.

At the core of this transformation lies customer engagement, which bridges businesses and their target audience [5]. The term encompasses how customers interact with a brand through cognitive

History: Received: 1 April 2025; Revised: 6 June 2025; Accepted: 9 June 2025; Published: 26 June 2025
* Correspondence: niyom.su@ssru.ac.th

involvement, emotional connection, or behavioral participation. In this sense, engagement goes beyond mere purchases—it reflects how much customers are invested in the brand and its offerings. Businesses that fail to prioritize customer engagement risk losing relevance in a crowded and competitive marketplace.

The importance of customer engagement can be understood through the Stimuli-Organism-Response (SOR) model. This framework explains how external environmental factors influence internal customer responses and ultimately drive specific outcomes [6]. This model identifies three primary environmental stimuli—social interaction, information quality, and perceived Value—that shape customer engagement. These stimuli activate the customer's cognitive, emotional, and behavioral dimensions of engagement, collectively called the "customer organism" in the model. The engagement, in turn, drives key outcomes, such as repurchase intentions and electronic word-of-mouth (eWOM), both of which are essential for fostering long-term customer loyalty and advocacy.

By addressing these questions, the study aims to comprehensively understand the factors driving customer engagement and their subsequent influence on customer behaviors. These insights will advance the academic discourse on customer engagement and offer practical strategies for businesses seeking to optimize their engagement efforts in a competitive digital marketplace. Thus, we proposed the research questions as follows:

1. How do social interaction affects customer engagement?
2. How does information quality affects customer engagement?
3. How does perceived value affects customer engagement
4. What is the relationship between customer engagement dimensions and repurchase intention or eWOM?

2. Literature Review and Conceptual Development

2.1. Stimulus-Organism-Response (SOR) theory

The Stimulus-Organism-Response (SOR) theory, initially introduced by Mehrabian and Russell [7] is a foundational theoretical framework that explains the relationship between external environmental stimuli, internal psychological states, and behavioral responses.

The SOR model thus provides a structured framework for understanding the progression from external influences to internal psychological processing and ultimately to action. The adaptability of the SOR theory has made it a cornerstone in consumer behavior research, where it has been applied to various contexts, including retail environments, digital marketing, and social commerce platforms. Its ability to link external environmental factors to specific consumer actions through internal mediation makes it a powerful tool for examining the mechanisms underlying decision-making.

In traditional retail environments, the SOR framework has been widely used to study how store atmospherics influence shopper behaviour [8]. Research has shown that elements such as lighting, music, layout, and scent can serve as powerful stimuli that evoke specific emotional and cognitive reactions [9]. For example, pleasant lighting and soothing music can create a relaxed shopping atmosphere, leading to higher levels of satisfaction and longer store visits. These internal states, in turn, encourage behaviors such as increased spending or brand loyalty Robert and John [10] expanded on the SOR model by emphasizing the role of emotional states—pleasure, arousal, and dominance—in shaping consumer behavior. Their work highlighted how retailers could strategically design store environments to elicit desired emotional responses, thereby influencing purchasing behavior. The rise of digital commerce has further expanded the applicability of the SOR theory. In online shopping contexts, stimuli often take the form of website design, product information, and user-generated content. These elements serve as critical touchpoints for attracting and retaining customers in the absence of physical interaction. For instance, Kim and Ko [11] demonstrated that website aesthetics, including layout, color schemes, and navigation ease, significantly impact consumers' emotional states and perceptions of trustworthiness. Positive organismic states, such as satisfaction and confidence, increase the likelihood of purchasing and revisiting the website.

Moreover, online reviews, ratings, and recommendations act as powerful stimuli that influence cognitive and emotional processing. Accurate and relevant reviews enhance trust and reduce perceived risk, while irrelevant or negative reviews can evoke skepticism and deter purchase decisions.

Social commerce platforms, such as Xiaohongshu, provide a particularly rich context for applying the SOR framework. These platforms integrate social networking features with e-commerce functionality, creating a dynamic environment where social interactions, information quality, and perceived value serve as key stimuli. On Xiaohongshu, user-generated content such as reviews, product recommendations, and lifestyle posts acts as a primary stimulus that drives consumer engagement. Internal processing occurs as users evaluate the credibility, relevance, and emotional appeal of the content. Positive organismic states—such as trust, enjoyment, and perceived usefulness—encourage behaviors like repurchase intentions and electronic word-of-mouth (eWOM). For example, Xia and Shannon [12] found that the frequency and quality of social interactions on social commerce platforms significantly influence emotional engagement. Consumers who perceive high levels of social support and information relevance are more likely to feel emotionally connected to the platform, leading to behaviors such as sharing positive reviews and recommending products to peers. The SOR framework has also been instrumental in shaping marketing strategies aimed at enhancing customer experiences and driving conversions. Marketers leverage stimuli such as personalized advertisements, interactive content, and real-time chat support to evoke positive organismic states in consumers. For example, personalized email campaigns that address customers by name and offer tailored product recommendations serve as stimuli that foster emotional engagement. When consumers perceive these efforts as thoughtful and relevant, they experience increased satisfaction and trust, resulting in higher response rates and conversion rates.

2.2. Social Interaction and Customer Engagement

Social interaction is fundamental to human behavior and critical to shaping customer engagement. In marketing and consumer behavior, social interaction refers to the communication, collaboration, and connection between individuals within a community, whether in-person or through digital platforms. Research has demonstrated that meaningful social interactions positively influence customer engagement by fostering trust, emotional connection, and a sense of belonging. This section explores empirical evidence and findings on the impact of social interaction on customer engagement across various industries and settings.

Pavlou and Dimoka [13] examined the role of social interaction in online trust formation. The findings indicate that e-commerce platforms that facilitate social interactions, such as customer reviews and Q&A forums, significantly enhance trust and engagement. Social interaction also plays a crucial role in customer retention by enhancing the overall customer experience. Verhoef, et al. [14] examined the impact of social interaction on customer relationship management (CRM). The findings suggest that social interactions, such as personalized communication and proactive engagement, significantly improve customer retention rates.

Social interaction profoundly impacts long-term business outcomes, including customer loyalty, advocacy, and revenue growth. Villanueva, et al. [15] examined the role of social interaction in customer acquisition and retention. The findings suggest that customers acquired through social interactions exhibit higher lifetime value and loyalty than traditional advertising. Berger, et al. [16] explored the relationship between social interaction and product sales. The research revealed that social interactions create a ripple effect, where initial conversations trigger additional discussions and purchases, amplifying their impact over time. These findings highlight the strategic importance of leveraging social interaction to drive sustainable growth. Thus, we proposed the hypothesis as below:

$H_{1a:}$ Social Interaction Positively Influences Cognitive Engagement

$H_{1b:}$ Social Interaction Positively Influences Emotional Engagement

$H_{1c:}$ Social Interaction Positively Influences Behavioral Engagement

Edelweiss Applied Science and Technology
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2.3. Information Quality and Customer Engagement

Information quality is critical to customer engagement, particularly in the digital era, where consumers rely heavily on information to make informed decisions. Relevance is a key attribute of information quality that directly influences customer engagement. Ho, et al. [17] examined the impact of personalization on information quality and engagement in e-commerce settings. The research revealed that customers who receive tailored recommendations based on their preferences and behavior exhibit higher satisfaction and engagement levels. For example, platforms like Netflix and Spotify leverage personalized recommendations to deliver relevant content, fostering stronger customer relationships. Timeliness, another crucial aspect of information quality, is vital in maintaining customer engagement. Aslam, et al. [18] identified timeliness as a core dimension of data quality, emphasizing its importance in meeting customer expectations. Their findings suggest that providing up-to-date, real-time information enhances customer satisfaction and loyalty. Clarity and ease of understanding are essential attributes of information quality that influence customer engagement. Albarq [19] examined the role of information clarity in user satisfaction with digital platforms. Their findings indicate that customers are more likely to engage with brands that provide clear and easy-to-understand information, reducing cognitive load and enhancing the user experience. Thus, we proposed the hypothesis as below:

H_{2a}: Information Quality Positively Influences Cognitive Engagement

H_{2a}: Information Quality Positively Influences Emotional Engagement

H_{2a}: Information Quality Positively Influences Behavioral Engagement

2.4. Perceived Value and Customer Engagement

Perceived value is a cornerstone of customer engagement, encompassing the customer's assessment of the benefits they receive relative to the costs incurred. It is a multifaceted concept integrating functional, emotional, social, and experiential dimensions. The perceived value significantly shapes customer attitudes, behaviors, and engagement levels, particularly in competitive markets where differentiation often hinges on delivering superior value. This section reviews empirical evidence and findings on how perceived value positively influences customer engagement across various industries and contexts.

Functional value, the practical benefits of a product or service, is critical in driving customer engagement Xia and Shannon [20]. Homburg and Baumgartner [21] highlight the importance of functional value in shaping customer perceptions and behaviors. Their findings suggest that customers who perceive a product or service as offering superior functionality and utility are more likely to engage with the brand. Emotional value, derived from the feelings or affective states elicited by a product or service, significantly enhances customer engagement. Xu and Xia [22] identifies emotional value as a key dimension of perceived value that fosters stronger customer-brand relationships. Customers who experience positive emotions, such as joy, excitement, or satisfaction, are more likely to engage with the brand. Laroche, et al. [23] highlight the importance of social value in fostering brand community participation and engagement. Customers who perceive social benefits, such as enhanced status or belonging, are more likely to interact with the brand and its community. Thus, we proposed the hypothesis as below:

H_{3a}: Perceived Value Positively Influences Cognitive Engagement.

H_{3b}: Perceived Value Positively Influences Emotional Engagement.

H_{3c}: Perceived Value Positively Influences Behavioral Engagement.

2.5. Customer Engagement and Repurchase Intention

Customer engagement, defined as the emotional, cognitive, and behavioral investment customers make in their interactions with a brand, has been widely recognized as a key driver of repurchase intention. Repurchase intention reflects a customer's willingness to buy a product or service from the same brand in the future. Various empirical studies across industries and contexts have substantiated the positive relationship between customer engagement and repurchase intention. This section explores the evidence and findings demonstrating how customer engagement fosters repurchase intentions and contributes to long-term business success.

Emotional engagement is crucial in strengthening the bond between customers and brands, enhancing repurchase intentions. Hollebeek, et al. [24] highlight the impact of emotional engagement on customer loyalty and retention. The findings suggest that customers who develop strong emotional connections with a brand are more likely to exhibit repurchase behaviors. Cognitive engagement, which involves customers' mental investment in understanding and evaluating a brand, significantly influences repurchase intention. Brodie, et al. [25] identified cognitive engagement as a key antecedent of customer loyalty. The study found that customers who invest time and effort in learning about a brand's offerings are more likely to perceive its value and engage in repeat purchases. Behavioral engagement, characterized by customers' active participation in brand-related activities, directly influences repurchase intention. So, et al. [26] explored the role of behavioral engagement in the hospitality industry. The research revealed that customers who frequently interact with a brand through loyalty programs, reviews, or social media are more likely to repurchase. For example, hotel chains that reward repeat stays with points or exclusive benefits foster higher behavioral engagement and repurchase intentions. Thus, we proposed the hypothesis as below:

H_4: Customer engagement positively influences repurchase intention.

2.6. Customer Engagement and eWOM

Customer engagement, characterized by the emotional, cognitive, and behavioral investment customers make in their interactions with a brand, plays a crucial role in generating electronic word-of-mouth (eWOM). eWOM, defined as the dissemination of opinions, reviews, and recommendations about products, services, or brands through digital channels, has emerged as a powerful driver of consumer decision-making and brand reputation. Empirical research consistently demonstrates that engaged customers are more likely to create and share eWOM, amplifying a brand's reach and influence. This section explores the empirical evidence and findings that substantiate the positive relationship between customer engagement and eWOM across various contexts and industries.

Emotional engagement, the affective bond customers form with a brand, significantly influences their propensity to share eWOM. [24] highlight that emotionally engaged customers experience heightened enthusiasm and attachment, motivating them to share their positive experiences online. Cognitive engagement, which involves customers' mental investment in understanding and evaluating a brand, also drives eWOM. The study found that customers with high behavioral engagement are more likely to generate eWOM, as their active involvement reinforces their loyalty and advocacy. Abzari, et al. [1] examined behavioral engagement in the hospitality industry and its impact on eWOM. The research revealed that customers who frequently engage with a brand through loyalty programs, social media interactions, or on-site activities are more likely to leave positive reviews and recommendations. For instance, hotels encouraging guests to share their experiences on social media amplifies their eWOM reach. Thus, we proposed the hypothesis as below:

H_5: Customer Engagement Positively Influences eWOM

Based on the hypotheses development, we proposed our conceptual framework as below:

ISSN: 2576-8484
Vol. 9, No. 6: 2400-2423, 2025
DOI: 10.55214/25768484.v9i6.8406

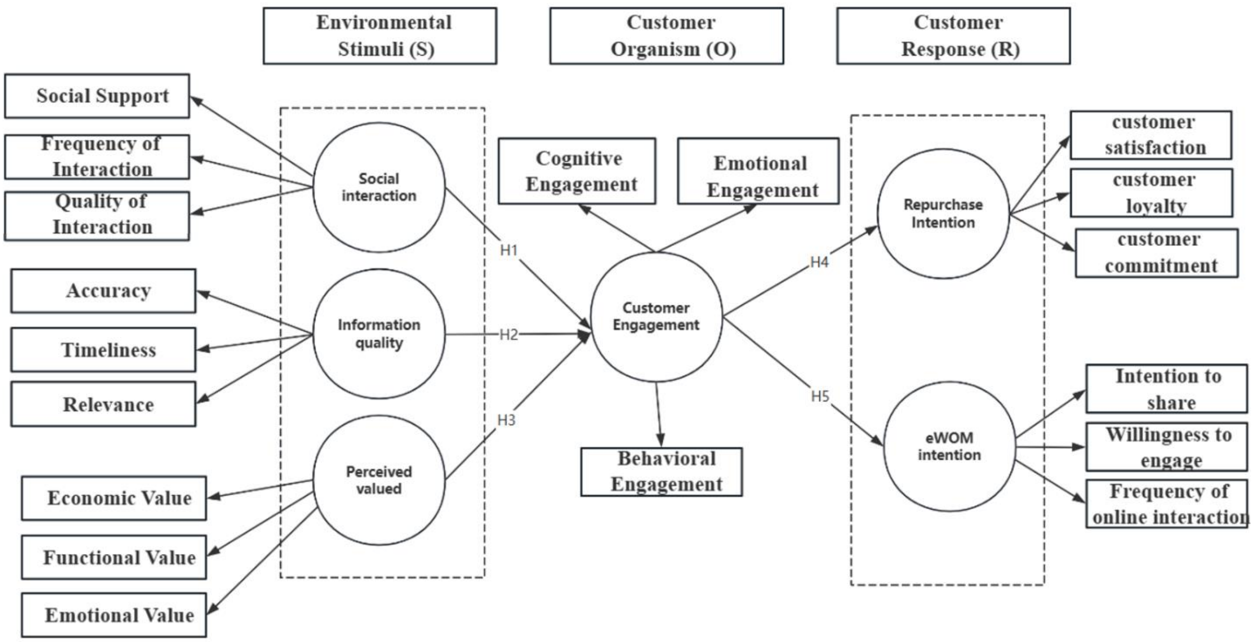

Figure 1.
The proposal conceptual framework.

3. Methodology

This study employs a mixed-methods research design integrating both quantitative and qualitative approaches to comprehensively examine the role of customer engagement in enhancing repurchase intention and electronic word-of-mouth (eWOM) within the framework of the Stimulus-Organism-Response (S-O-R) model in the Xiaohongshu platform. The mixed-methods approach enables a deeper understanding of how social interaction, information quality, and perceived value influence cognitive, emotional, and behavioral engagement and their subsequent impact on customer responses. The quantitative phase establishes relationships between key variables, while the qualitative phase provides deeper insights into customer perceptions and experiences.

3.1. Quantitative Phase

3.1.1. Research Design

A robust research design is the cornerstone of any empirical study, providing the framework for systematically investigating research questions, validating theoretical constructs, and ensuring the reliability and validity of findings. This study adopts a quantitative research design to test hypotheses derived from the conceptual framework, exploring the relationships between environmental stimuli, customer engagement, and behavioral responses such as repurchase intention and electronic word-of-mouth (eWOM). The following study outlines the research approach, target population, sampling strategies, data collection methods, measurement instruments, and analytical techniques employed in this study.

Quantitative research focuses on the objective measurement and numerical analysis of variables to identify patterns, relationships, and causal effects. The study aims to test hypotheses on the effects of social interaction, information quality, and perceived value on customer engagement and subsequent behavioral responses. Quantitative methods facilitate the precise testing of these relationships through statistical techniques. Quantitative research accurately measures relationships between independent (environmental stimuli) and dependent variables (customer engagement, repurchase intention, and eWOM), providing robust insights into the conceptual framework.

DOI: 10.55214/25768484.v9i6.8406

3.1.2. Target Population and Sampling Design

The study focuses on the target population of active users of Xiaohongshu, a prominent social commerce platform that combines social networking with e-commerce in Shanghai, China. Xiaohongshu has gained considerable traction among users who actively share product reviews, lifestyle tips, and shopping experiences, making it a suitable platform for investigating customer engagement and its influence on repurchase intentions and electronic word-of-mouth (eWOM). The choice of this population aligns with the study's primary goal of examining how social interaction, information quality, and perceived value influence customer engagement and its subsequent outcomes. The target population includes users who have made at least one purchase through Xiaohongshu within the past six months in Shanghai, China.

A purposive sampling technique was employed to study the target population effectively. Purposive sampling is a non-probability sampling method that allows researchers to select participants who meet specific criteria relevant to the study. The study employs a simple random sampling method to determine an appropriate sample size, ensuring representativeness while minimizing potential bias. The sample size is calculated using [5] formula, which is widely applied in social science research when the total population is known. The formula used is:

$$n = \frac{N}{1 + N(e)^2}$$

where:

n is the sample size,

N is the total population under study,

e represents the margin of error (set at 0.05)

This study's estimated total population is 13,563, leading to a calculated sample size of approximately 388.51. To enhance reliability and accommodate potential non-responses, the final sample size for this study is 407 participants.

3.1.3. Data Collection

The data collection for this study was conducted using a structured online survey distributed to the selected participants through Xiaohongshu's platform and associated communication channels. This method ensures accessibility, efficiency, and the ability to reach a geographically dispersed population of active users. The survey was designed to capture quantitative data on social interaction, information quality, perceived value, customer engagement dimensions (cognitive, emotional, and behavioral), and key behavioral outcomes (repurchase intention and eWOM). The survey instrument will consist of closed-ended questions using a five-point Likert scale to measure the intensity of respondents' perceptions and behaviors. This scale is appropriate for capturing variations in user attitudes and engagement levels.

3.1.4. Data Analysis

This study employs a Structural Equation Modeling (SEM) approach to examine the relationships among latent variables. SEM is a powerful multivariate statistical technique that allows for the analysis of complex relationships while simultaneously accounting for measurement errors. The study follows a rigorous process, including data collection, reliability and validity assessment, and structural model evaluation.

To ensure the accuracy and consistency of the measurement tools, the study evaluates internal consistency reliability and construct validity through several statistical tests.

First, Cronbach's Alpha (α) assesses internal consistency reliability. Second, Composite Reliability (CR) is examined to complement Cronbach's Alpha. In addition to reliability, the study also evaluates construct validity, which determines whether the measurement tool accurately captures the intended theoretical constructs.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 6: 2400-2423, 2025
DOI: 10.55214/25768484.v9i6.8406

Convergent validity measures the extent to which different indicators of the same construct are positively correlated. This is typically assessed using Average Variance Extracted (AVE), where a value above 0.5 indicates that the construct explains more than half of the variance in its indicators [27]. Discriminant validity, on the other hand, ensures that each construct is distinct from other constructs in the model. This is evaluated by comparing the square root of AVE with the correlations between constructs. If the square root of AVE is greater than the correlation between two constructs, discriminant validity is established, confirming that the constructs measure separate concepts. Ensuring strong discriminant validity is crucial for preventing multicollinearity issues and enhancing the theoretical soundness of the model.

The measurement model is assessed using Confirmatory Factor Analysis (CFA), which verifies the factor structure of the constructs. Factor loadings, reliability indicators (Cronbach's Alpha and CR), and validity measures (AVE and discriminant validity) are examined to ensure a robust measurement framework.

The study tests the structural model by analyzing the relationships between latent variables. This involves evaluating path coefficients to determine the strength and direction of hypothesized relationships. Additionally, R^2 values are used to assess the explanatory power of the independent variables on the dependent variables. Model fit indices, such as Chi-square (χ^2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR), are used to determine how well the model aligns with the observed data [28].

By utilizing Structural Equation Modeling (SEM), this study comprehensively analyzes the relationships among latent variables while accounting for measurement errors. The rigorous assessment of reliability and validity ensures the credibility of the findings, while the structural model analysis offers valuable insights into the hypothesized relationships.

3.2. Qualitative analysis

3.2.1. In-depth Interviews

To supplement the quantitative findings, semi-structured interviews will be conducted with 15-20 Xiaohongshu users to gain deeper insights into their engagement behaviors and decision-making processes. The use of in-depth interviews allows for a more nuanced exploration of customer attitudes, motivations, and contextual influences that may not be fully captured through the survey. These interviews aim to uncover underlying themes related to customer engagement and its effect on repurchase intention and eWOM. Hence, the researchers chose the 17 informants to interview. A semi-structured interview guide was developed, ensuring that key research areas are covered while allowing for response flexibility.

To maintain ethical integrity, all selected participants were fully informed about the study's objectives, the voluntary nature of their participation, and the confidentiality of their responses before providing consent. Interviewees will also have the option to withdraw at any stage without consequences. This rigorous sampling strategy will ensure that the study captures a comprehensive understanding of engagement behaviors on Xiaohongshu.

3.2.2. Data Analysis

The qualitative data was analyzed using thematic analysis, facilitated by NVivo software, to systematically identify key themes and patterns related to customer engagement and responses. These themes were reviewed for coherence, relevance, and alignment with the research objectives, undergoing refinement, merging, or splitting to ensure consistency across the dataset. Once finalized, themes will be clearly articulated and conceptualized to capture key findings on the dimensions of social interaction, information quality, perceived value, and customer engagement. The final themes of the research questions will be interpreted, with direct participant quotations used to substantiate findings and enhance validity.

4. Research Results

4.1. Stage I Quantitative Analysis

4.1.1. Respondent Profiles

Based on the data screening, the researchers deleted some unclear data. The total number of respondents is 407 after the data screening. Table 1 shows the demographic information of the people who are active users in Shanghai, China.

Table 1.
Demographic information (N=407).

Items	Category	Frequency	Percentage
Gender	Male	178	43.7%
	Female	229	56.3%
Age	18-25 years old	24	5.9%
	26-30 years old	152	37.3%
	30-35 years old	131	32.2%
	36-40 years old	83	20.4%
	40 years old and above	17	4.2%
Education level	Junior college degree or below	71	17.4%
	Bachelor's degree	210	51.6%
	Master's degree	114	28.0%
	Doctor's degree	12	2.9%
Income	$20,000 or below	52	12.8%
	$20,001 to $30,000	214	52.6%
	$30,001 to $40,000	115	28.3%
	More than $40,001	26	6.4%

Table 1 shows the demographic profile of the 407 respondents and offers key context for understanding the study's findings. The sample includes 43.7% males (n=178) and 56.3% females (n=229), which is consistent with Xiaohongshu's predominantly female user base. Most respondents are young adults, with 37.3% aged 26–30 and 32.2% aged 30–35. Most hold a bachelor's degree (51.6%), followed by 28.0% with a master's degree. Regarding income, 52.6% earn between $20,001–$30,000 annually, with 28.3% earning $30,001–$40,000. These figures reflect Xiaohongshu's appeal to young, educated, and middle-income urban users, aligning well with the platform's core demographic.

4.2. Confirmatory Factor Analysis (CFA)

Table 2.
The result of the Confirmatory Factor Analysis (CFA).

Constructs	Items	Factor Loading	AVE	Cronbach's Alpha
Social Support	SS1	0.594	0.637	0.875
	SS2	0.671		
	SS3	0.684		
	SS4	0.725		
Frequency of interaction	FOI1	0.693	0.672	0.891
	FOI2	0.641		
	FOI3	0.713		
	FOI4	0.517		
Quality of interaction	QOI1	0.65	0.672	0.890
	QOI2	0.596		
	QOI3	0.688		
	QOI4	0.632		
Accuracy	AC1	0.688	0.638	0.875
	AC2	0.710		
	AC3	0.638		
	AC4	0.728		

DOI: 10.55214/25768484.v9i6.8406

Timeliness	TI1	0.641	0.669	0.890
	TI2	0.609		
	TI3	0.578		
	TI4	0.675		
Relevance	RE1	0.685	0.692	0.899
	RE2	0.539		
	RE3	0.574		
	RE4	0.625		
Economic Value	EV1	0.683	0.625	0.869
	EV2	0.679		
	EV3	0.735		
	EV4	0.653		
Functional Value	FV1	0.651	0.626	0.87
	FV2	0.589		
	FV3	0.624		
	FV4	0.635		
Emotional Value	EMV1	0.594	0.598	0.856
	EMV2	0.676		
	EMV3	0.663		
	EMV4	0.603		
Cognitive Engagement	CE1	0.592	0.677	0.892
	CE2	0.586		
	CE3	0.524		
	CE4	0.557		
Emotional Engagement	EE1	0.554	0.725	0.913
	EE2	0.665		
	EE3	0.522		
	EE4	0.581		
Behavioral Engagement	BE1	0.634	0.691	0.898
	BE2	0.568		
	BE3	0.662		
	BE4	0.500		
Customer Satisfaction	CS1	0.614	0.711	0.908
	CS2	0.519		
	CS3	0.618		
	CS4	0.634		
Customer loyalty	CL1	0.594	0.71	0.907
	CL2	0.612		
	CL3	0.567		
	CL4	0.573		
Customer Commitment	CC1	0.618	0.702	0.904
	CC2	0.521		
	CC3	0.555		
	CC4	0.617		
Intention to Share	ITS1	0.581	0.754	0.924
	ITS2	0.572		
	ITS3	0.569		
	ITS4	0.586		
Willingness to Engage	WTE1	0.731	0.663	0.885
	WTE2	0.748		
	WTE3	0.736		
	WTE4	0.587		
Frequency of Online Interaction	FOOI1	0.689	0.664	0.887
	FOOI2	0.506		
	FOOI3	0.706		
	FOOI4	0.634		

Table 2 shows that the measurement model was assessed for reliability and validity using factor loadings, Cronbach's Alpha, and Average Variance Extracted (AVE). All factor loadings exceeded 0.50, demonstrating acceptable item reliability, with most values between 0.55 and 0.73. While a few items had lower loadings, they were retained for theoretical relevance. Cronbach's Alpha values for all constructs were above 0.70, confirming strong internal consistency, especially for Emotional Engagement ($\alpha = 0.913$), Intention to Share ($\alpha = 0.924$), and Customer Satisfaction ($\alpha = 0.908$). AVE values ranged from 0.598 to 0.754, meeting the 0.50 threshold for convergent validity. These findings confirm that the measurement model has sound psychometric properties and is appropriate for structural modeling. The result is also shown in Figure 2.

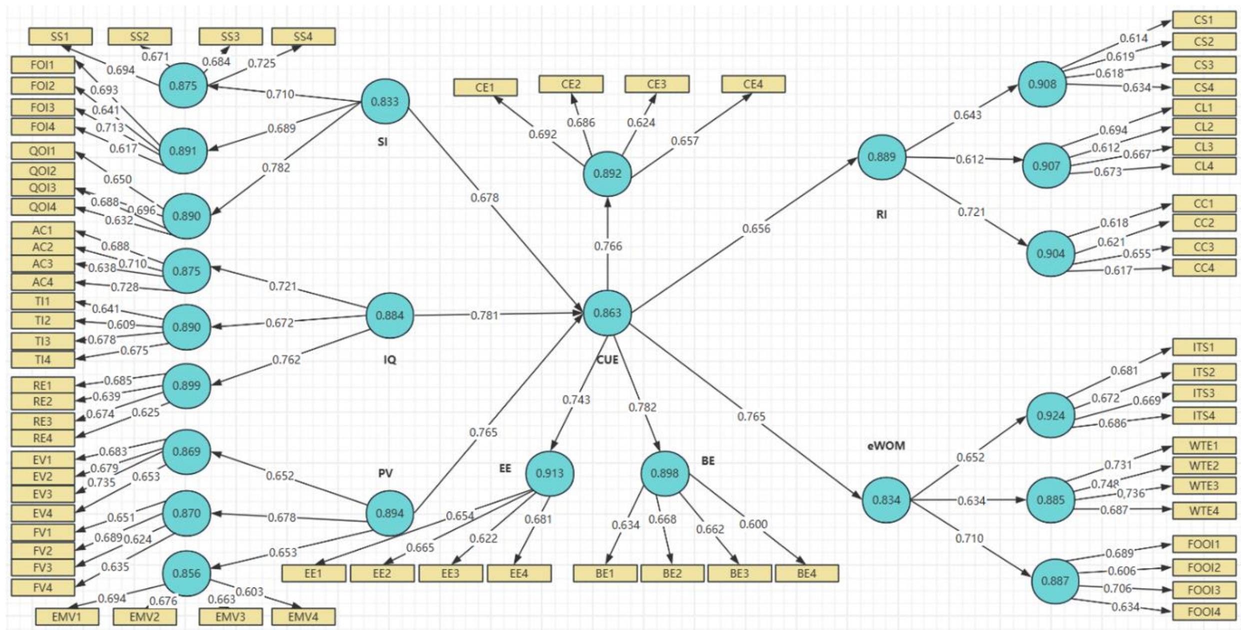

Figure 2.
The CFA result of the modeling.

Table 3.
Discriminant validity analysis.

Constructs	SS	FOI	QO	AC	TI	RE	EV	FV	EMV	CEN	RI	eWOM
SS	0.798											
FOI	0.256	0.819										
QO	0.258	0.340	0.811									
AC	0.146	-0.008	0.325	0.806								
TI	0.109	0.132	0.070	0.405	0.822							
RE	0.163	0.181	0.114	0.346	0.408	0.829						
EV	0.089	0.192	0.162	0.484	0.523	0.553	0.788					
FV	0.330	-0.059	0.106	0.165	0.112	0.168	0.120	0.797				
EMV	0.020	0.226	-0.086	-0.052	0.154	0.166	0.096	0.283	0.782			
CEN	0.157	0.333	0.187	0.179	0.207	0.176	0.259	0.365	0.235	0.818		
RI	0.234	0.403	0.224	0.157	0.337	0.264	0.306	0.296	0.266	0.622	0.856	
eWOM	0.121	0.011	0.151	0.153	0.171	0.140	0.155	0.137	0.141	0.098	0.296	0.835

***Note*:** The square root of AVE for each latent construct is given in diagonals.

Table 3 is to assess discriminant validity, the study employed the Fornell-Larcker criterion, which requires that the square root of each construct's AVE exceed its correlations with other constructs. As shown in Table 3, this condition is consistently met. For example, Social Support ($\sqrt{AVE} = 0.798$) is

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 6: 2400-2423, 2025
DOI: 10.55214/25768484.v9i6.8406

greater than its highest correlation (0.258), and Accuracy (√AVE = 0.806) exceeds its correlations with related constructs like Timeliness (0.405) and Relevance (0.346). Similarly, Customer Commitment (0.856) and eWOM Intention (0.835) display apparent discriminant validity, with lower correlations across all constructs. All 14 constructs—including Economic Value, Functional Value, Emotional Value, and both engagement dimensions—demonstrate strong discriminant validity. These results confirm that the constructs are conceptually distinct, providing a solid foundation for the subsequent structural model analysis.

Table 4.
Goodness-of-fit' statistics for the structural model.

Model Fit Indicators	Required Values	Model Result	Remarks
'CMIN/DF'	1-3	1.53	Acceptable
'RMSEA'	<0.08	0.036	Good
'SRMR'	<0.05	0.036	Good
'GFI'	>0.90	0.914	Good
'CFI'	>0.90	0.938	Excellent
'IFI'	>0.90	0.982	Excellent
'TLI'	>0.90	0.932	Good

Several fit indices were examined to assess the structural model's adequacy. The CMIN/DF ratio was 1.53, within the acceptable range of 1–3, indicating good model parsimony. RMSEA and SRMR values were both 0.036, below the recommended cutoffs of 0.08 and 0.05, respectively, suggesting a strong fit with low residual error. Incremental fit indices also confirmed model adequacy: GFI (0.914), CFI (0.938), IFI (0.982), and TLI (0.932) all exceeded the 0.90 benchmark. These results demonstrate a robust and well-fitting structural model, providing a reliable foundation for hypothesis testing.

4.2.1. Structural Equation Modelling

Table 5.
Hypotheses test result.

Hypotheses	Estimate	P	Supported (Yes/No)
***H1a**: Social Interaction Positively Influences Cognitive Engagement*	0.364	0.003	Yes
***H1b**: Social Interaction Positively Influences Emotional Engagement*	0.199	0.000	Yes
***H1c**: Social Interaction Positively Influences Behavioral Engagement*	0.522	0.000	Yes
***H2a**: Information Quality Positively Influences Cognitive Engagement*	0.183	0.000	Yes
***H2a**: Information Quality Positively Influences Emotional Engagement*	0.143	0.010	Yes
***H2a**: Information Quality Positively Influences Behavioral Engagement*	0.167	0.002	Yes
***H3a**: Perceived Value Positively Influences Cognitive Engagement*	0.288	0.000	Yes
***H3b**: Perceived Value Positively Influences Emotional Engagement*	0.550	0.000	Yes
***H3c**: Perceived Value Positively Influences Behavioral Engagement*	0.210	0.000	Yes
***H4:** Customer engagement positively influences repurchase intention.*	0.622	0.000	Yes
***H5**: Customer Engagement Positively Influences eWOM*	0.098	0.048	Yes

The final stage of the structural equation modeling tested the hypothesized paths among constructs using standardized path coefficients in Table 5. All hypotheses were supported at statistically significant levels ($p < 0.05$). Social Interaction significantly influenced Cognitive ($\beta = 0.364$), Emotional ($\beta = 0.199$), and Behavioral Engagement ($\beta = 0.522$), confirming H1a–H1c. Information Quality also positively impacted all engagement dimensions—Cognitive ($\beta = 0.183$), Emotional ($\beta = 0.143$), and Behavioral ($\beta = 0.167$)—supporting H2a–H2c. Perceived value showed strong effects on Cognitive ($\beta = 0.288$), Emotional ($\beta = 0.550$), and Behavioral Engagement ($\beta = 0.210$), validating H3a–H3c. Customer Engagement significantly predicted Repurchase Intention ($\beta = 0.622$, $p = .000$) and had a weaker but

ISSN: 2576-8484
Vol. 9, No. 6: 2400-2423, 2025
DOI: 10.55214/25768484.v9i6.8406

still significant effect on eWOM (β = 0.098, p = .048), supporting H4 and H5. These results confirm that platform-driven stimuli effectively shape engagement, which drives user loyalty and advocacy.

4.2.2. Stage 2 Qualitative Analysis

To complement and strengthen the quantitative findings derived from structural equation modeling, this section presents an in-depth qualitative analysis to uncover users' nuanced perceptions and lived experiences engaging with Xiaohongshu. 17 in-depth interviews were conducted in Table 6, with participants ranging from 20 to 38 years of age. The sample was demographically consistent with the survey respondents: primarily female (53%) and male (47%), holding at least a bachelor's degree. All participants used Xiaohongshu for over a year and were familiar with its shopping, content-sharing, and community interaction functions.

Table 6.
Shows the informant's information about using the Xiaohongshu.

Number	Name	Age	Gender	Education
1	Informant A	27	Male	Bachelor
2	Informant B	32	Male	Master
3	Informant C	29	Female	Master
4	Informant D	30	Female	Ph.d
5	Informant E	31	Male	Bachelor
6	Informant F	27	Female	Bachelor
7	Informant G	23	Male	Master
8	Informant H	33	Male	Master
9	Informant I	37	Male	Bachelor
10	Informant J	35	Female	Bachelor
11	Informant K	32	Female	Bachelor
12	Informant L	38	Male	Ph.d
13	Informant M	20	Female	Bachelor
14	Informant N	33	Male	Master
15	Informant O	38	Female	Bachelor
16	Informant P	31	Female	Master
17	Informant Q	26	Female	Master

4.2.3. The Influence of Social Interaction on Customer Engagement (H1a, H1b, H1c)

The first theme that emerged prominently from the qualitative interviews centers on how social interaction on Xiaohongshu functions as a catalyst for engaging users cognitively, emotionally, and behaviorally. Participants consistently described the platform not merely as a transactional or content-sharing space but as a community-driven ecosystem where social dynamics—such as peer support, discussion threads, real-time feedback, and influencer interactions—played an integral role in shaping their engagement behaviors.

Participants repeatedly emphasized that Xiaohongshu's socially constructed environment demanded heightened attention and focus, supporting H1a. One user remarked:

"When I read others' posts or reviews, especially about skincare or travel, I concentrate much more than on other apps. It's not just scrolling—I'm reading carefully, comparing comments, and thinking about what I want to do or buy." (Participant 4, Female, 26 years old)

Several users noted that their mental involvement increased when they participated in discussions, especially in areas like health, lifestyle, or beauty—topics where they sought personalized insights. The interactive nature of posts, such as the ability to "collect," "comment," and "ask questions," triggered an evaluative cognitive process among users. In line with the quantitative finding that social interaction positively influences cognitive engagement (β = 0.364, p = .003), the qualitative data confirms that social stimuli on Xiaohongshu heighten mental focus, leading to deeper information processing and decision-making.

Emotional engagement, as hypothesized in H1b, was deeply intertwined with the sense of community and emotional resonance that users experienced during interactions. Many users reported feeling emotionally connected to certain influencers or fellow users due to shared life experiences, preferences, or values. One interviewee described:

"There's a girl I follow who talks about managing anxiety and skincare. I feel like I know her. Her comments section is always warm and supportive. I feel safe sharing my thoughts there." (Participant 11, Female, 24 years old)

Such narratives reveal that positive emotions such as empathy, trust, comfort, and inspiration are evoked when users engage in meaningful social interactions. The platform's peer-driven nature—unlike purely commercial social media—fosters a supportive emotional climate, particularly in lifestyle, health, and self-improvement communities. These emotions enhance users' emotional commitment to the platform, mirroring the quantitative result that social interaction significantly predicts emotional engagement (β = 0.199, p = .000). The affective bonds cultivated through interaction act as emotional anchors, keeping users involved with the platform.

The third dimension of customer engagement, behavioral, found the strongest support from the interview data, validating H1c (β = 0.522, p = .000). Participants described behavioral engagement not only in terms of content consumption but also active content creation, commenting, and recommending posts. A recurring theme was that social interaction encouraged them to return to the app frequently and contribute content themselves.

"I started by just reading product reviews, but now I also post my own opinions—especially when I feel strongly about something. The replies and likes I get make me want to keep sharing." (Participant 8, Male, 29 years old)

Moreover, participants described daily routines around Xiaohongshu usage, such as checking the platform before buying products, browsing influencer content after work, or reading health advice in the mornings. These behaviors suggest that social interactions have become a habitual motivator, encouraging consistent behavioral participation.

"It's become part of my day, like checking messages or news. I'll just open Xiaohongshu to see what people are talking about or what's trending." (Participant 2, Female, 32 years old)

The positive reinforcement loop created through likes, saves, and replies also played a role in strengthening behavioral engagement. Interviewees described this social feedback as rewarding and validating, which reinforced continuous activity on the platform.

Thematic evidence strongly supports H1a, H1b, and H1c, confirming that social interaction serves as a powerful antecedent of customer engagement on Xiaohongshu.

4.2.4. The Influence of Information Quality on Customer Engagement (H2a, H2b, H2c)

The second key theme emerging from the qualitative data relates to the significance of information quality—encompassing accuracy, timeliness, and relevance—in shaping different dimensions of customer engagement. Across interviews, users repeatedly highlighted that the perceived quality of the content they encountered on Xiaohongshu profoundly influenced their mental involvement (cognitive engagement), emotional reaction (emotional engagement), and usage behaviors (behavioral engagement). These qualitative insights reinforce the quantitative evidence that information quality is a statistically significant antecedent of all three engagement dimensions (H2a–H2c).

Participants expressed that credible, specific, and actionable content on Xiaohongshu captured their attention more deeply than generic or sponsored material. In line with H2a (β = 0.183, p = .000), users described scenarios where they would spend considerable time reading, cross-referencing, and even saving detailed posts that they perceived as trustworthy.

"When I see a post that's really detailed—like someone comparing skincare routines with before-and-after photos—I focus a lot more. I'll even save it to read again later."

(Participant 6, Female, 25 years old)

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 6: 2400-2423, 2025
DOI: 10.55214/25768484.v9i6.8406

Interviewees explained that timely updates and consistent accuracy made them rely on Xiaohongshu for decision-making, particularly for beauty, health, and travel-related topics. This cognitive engagement manifests as deliberate reading, attention to detail, and critical comparison with other sources. As one participant noted:

"I usually check Xiaohongshu before I make any big purchase. I trust it more than other platforms because people provide honest feedback. That makes me pay more attention."

(Participant 12, Male, 34 years old)

These insights illustrate that perceived accuracy and usefulness of content serve as cognitive triggers, drawing users into sustained mental interaction with the platform's content.

The influence of information quality on emotional engagement was less pronounced than cognitive engagement but still supported through the emergence of emotional themes such as gratitude, trust, reassurance, and enjoyment. In support of H2b ($\beta = 0.143$, $p = .010$), participants explained that when content felt reliable and relevant, it made them feel more confident and satisfied emotionally.

"I feel more confident after reading some posts on Xiaohongshu. Especially when I'm unsure what to buy. When I find a trustworthy review, I feel relieved."

(Participant 9, Female, 30 years old)

Some users mentioned experiencing a sense of gratification when they discovered tips that solved real-life problems, like a skincare regimen that worked or affordable lifestyle hacks. This satisfaction was often expressed emotionally—users felt happy, thankful, or connected to the post's author. Others described feeling emotionally reassured by the shared experiences of others:

"It's not just about facts; it's about feelings. When someone shares how a product helped their acne, and I'm dealing with the same thing, it makes me feel seen and hopeful."

(Participant 1, Female, 22 years old)

The effect of high-quality information on behavioral engagement (H2c; $\beta = 0.167$, $p = .002$) was evident in how participants described frequent checking, saving, commenting, and sharing behavior. Information that was timely and tailored to their interests encouraged repeat visits and motivated action, such as trying a product, modifying routines, or creating content in response.

"If I find something useful, I often share it with my friends or repost it to my story. And sometimes, I'll comment to ask more questions or say thank you."

(Participant 5, Female, 28 years old)

Additionally, the structure of Xiaohongshu's algorithm, which promotes relevant and timely content, helped reinforce platform habits. Several users mentioned that they now start or end their day by browsing Xiaohongshu, as they trust the platform to provide up-to-date recommendations and helpful insights. This habitual engagement was described as triggered by content value rather than entertainment.

"I check Xiaohongshu daily because I know there will be something useful—whether it's a recipe, a product review, or someone's real story."

(Participant 13, Male, 35 years old)

Thus, information quality is not a passive background factor, but a key driver that initiates and reinforces behavioral patterns, turning one-time users into regular contributors and consumers.

Thematic analysis confirms that information quality significantly enhances all dimensions of customer engagement, providing robust support for hypotheses H2a, H2b, and H2c. Cognitive engagement is driven by attention to informative, accurate, and timely content. Emotional engagement arises from the reassurance, gratitude, and confidence users derive from meaningful and relevant posts. Behavioral engagement is reinforced through repeat interaction and content sharing prompted by high-quality information. These insights highlight that in the Xiaohongshu ecosystem, content quality functions as both a utility and a stimulus, reinforcing engagement across cognitive, emotional, and behavioral lines.

4.2.5. The Influence of Perceived Value on Customer Engagement (H3a, H3b, H3c)

The third major theme revealed by the qualitative interviews concerns the pivotal role of perceived value—comprising economic, functional, and emotional value—in driving customer engagement across all three dimensions. Participants repeatedly emphasized that Xiaohongshu provides not only a platform for discovery but also a value-rich environment that satisfies both practical and affective user needs. These findings reinforce the structural model results supporting H3a ($\beta = 0.288$, $p = .000$), H3b ($\beta = 0.550$, $p = .000$), and H3c ($\beta = 0.210$, $p = .000$), and offer deeper contextual understanding of how value perception translates into engagement behavior.

Participants demonstrated that cognitive engagement is significantly influenced by the practical utility and affordability of Xiaohongshu's offerings. Many respondents described the app as a "go-to decision-making companion," where they could find cost-effective solutions, reviews, and user experiences. The perception of economic value was not merely about discounts or pricing, but about the ability to make informed, money-saving decisions.

"Xiaohongshu saves me time and money. I don't need to try things blindly. If someone with similar skin recommends a product and it's affordable, I'll focus on that post carefully."

(Participant 3, Female, 27 years old)

Users also noted that Xiaohongshu helped them mentally filter options and structure their thinking, especially when planning purchases or organizing routines, such as meal prepping, skincare, or travel. This functional value deepened their mental engagement, leading them to concentrate more on reading, comparing, and evaluating content.

"I think through my plans while using the app. Like for travel—I build my itinerary just by reading others' posts and comments. It becomes a thinking tool, not just entertainment."

(Participant 10, Male, 31 years old)

These perspectives confirm that cognitive engagement is driven by the platform's role in enabling smarter, more efficient decision-making, aligning with H3a.

The emotional dimension of perceived value was another dominant theme. Participants expressed that Xiaohongshu evoked positive emotions such as joy, satisfaction, motivation, and even inspiration. This emotional engagement was linked not only to the content itself but to the interpersonal and experiential connections users felt while using the app.

"Some posts just make me happy—like when people share their fitness journey or decorate their homes creatively. It inspires me emotionally, not just logically."

(Participant 7, Female, 23 years old)

Users also described a sense of emotional reward when they could solve a personal need or discover something that improved their life. This sense of value extended beyond transactional benefits to include psychological enrichment, suggesting that Xiaohongshu is seen as emotionally meaningful and affirming, particularly in lifestyle, wellness, and identity-based communities.

"I follow a few girls who share about mental health and self-care. It's more than just content—it feels like a support group sometimes. That connection is valuable emotionally."

(Participant 15, Female, 28 years old)

These narratives lend strong qualitative support to H3b, indicating that emotional value leads to deep affective engagement with the platform.

The interviews also revealed that behavioral engagement is a natural outcome of perceived value, particularly when users feel that the platform helps them achieve personal goals or express themselves. Many users described routinely using the platform to apply tips, share experiences, and revisit content that they found valuable. Their motivation to act—to like, post, save, or comment—was closely tied to the sense that Xiaohongshu was useful and emotionally satisfying.

"When I find a post that really helps me—like a DIY hack or wellness advice—I want to give back by commenting or posting my version. It feels fair to contribute when I've gained something."

(Participant 6, Male, 30 years old)

ISSN: 2576-8484
Vol. 9, No. 6: 2400-2423, 2025
DOI: 10.55214/25768484.v9i6.8406

Behavioral engagement was also expressed through platform loyalty. Several users stated that they preferred Xiaohongshu over other social or shopping platforms because the perceived value was higher, prompting repeated interaction and advocacy.

"I keep going back because I trust it. I've had fewer bad purchases since I started using Xiaohongshu. So I use it more, and I tell others about it too."

(Participant 14, Female, 33 years old)

This reciprocal cycle of perceived value and behavioral engagement reinforces the quantitative finding that perceived value has a significant impact on user actions, thereby supporting H3c.

The qualitative findings clearly reinforce hypotheses H3a, H3b, and H3c, demonstrating that perceived value is a key determinant of cognitive, emotional, and behavioral engagement. Cognitive engagement stems from functional benefits like convenience, efficiency, and decision-making support. Emotional engagement arises from positive psychological responses to inspiring or personally meaningful content. Behavioral engagement is driven by users' motivation to act upon and reciprocate the value they receive. These insights further validate that perceived value is not only a motivator but a unifying force that sustains long-term engagement, making it a cornerstone of Xiaohongshu's user retention strategy.

4.2.6. The Influence of Customer Engagement on Repurchase Intention (H4)

The fourth major theme that emerged from the qualitative interviews demonstrates how the various dimensions of customer engagement—cognitive, emotional, and behavioral—collectively influence users' repurchase intention on Xiaohongshu. The hypothesis (H4), which was supported quantitatively with a strong and statistically significant path coefficient ($\beta = 0.622$, $p = .000$), finds equally compelling validation through in-depth user narratives. Participants consistently indicated that their continued purchases through Xiaohongshu were a direct outcome of their intense mental focus, emotional connection, and sustained interaction with the platform's content and community.

Several participants described their repurchase behavior as deliberate and informed, stemming from the trust they built through cognitively engaging content. Posts that offered detailed comparisons, user experiences, and transparent reviews were viewed as credible sources of product knowledge, which in turn gave users the confidence to make recurring purchases.

"There are certain accounts I follow that I trust completely. When they update their reviews on a brand or a product, I read it carefully. If I liked the last product they recommended, I'll definitely buy the next one."

(Participant 8, Female, 26 years old)

This indicates that cognitive engagement doesn't end at comprehension—it directly motivates action, particularly when users associate detailed content with product performance. The process of focusing, analyzing, and making mental comparisons increases the likelihood that users will return to buy again from the same seller or category. Xiaohongshu becomes a trusted decision aid, reinforcing long-term consumption cycles.

Emotional engagement was also a strong predictor of repurchase intention. Users described their repurchasing decisions as emotionally motivated, not just rational. When users felt pleasure, satisfaction, or connection with a brand or user recommendation on the platform, they were more likely to remain loyal to that product or store.

"I once bought a handmade candle from a small shop I found here. The post was so heartfelt, and when I received it, the product matched the emotion. I felt connected to the story—and I've reordered three times."

(Participant 12, Female, 31 years old)

In this case, repurchase was driven less by cost or utility and more by emotional resonance—a connection forged through content that reflected the user's values or emotions. This aligns with previous research that suggests affective loyalty often precedes behavioral loyalty, especially in community-driven platforms like Xiaohongshu.

Other users pointed out that emotionally positive experiences—such as feeling part of a like-minded group or gaining confidence from community feedback—enhanced their attachment to the platform, making it their preferred choice for future purchases. One participant summarized it succinctly:

"I could buy these items elsewhere, sure. But I don't want to. I trust Xiaohongshu because I feel like it's where I belong."

(Participant 5, Female, 29 years old)

Perhaps the clearest link to repurchase behavior emerged from behavioral engagement. Users who actively liked, commented, posted, and followed specific accounts were more likely to make repeat purchases. For them, Xiaohongshu had become embedded in daily habits and decision routines, reinforcing brand recall and consumption patterns.

"Every time I need something—makeup, home stuff—I check Xiaohongshu first. I already know the sellers I've bought from before, and I just go back. It's easy because I've saved their posts."

(Participant 10, Male, 34 years old)

For these users, behavioral engagement translates into platform stickiness, where Xiaohongshu becomes the default channel not only for information but for commerce. Repeat behavior, supported by familiar routines and successful past transactions, fosters a loop in which interactions lead to purchases, which in turn trigger further interaction.

Furthermore, features like content saving, reminders, and personalized feeds were frequently mentioned as functional enablers of repurchasing. These elements support the idea that behavioral engagement is reinforced through interface design that nudges users toward continued transactions.

"The app shows me updates from shops I've interacted with. It's like a gentle reminder to go back. I don't need to search again—I just click and buy."

(Participant 3, Female, 30 years old)

The qualitative findings provide strong empirical and narrative support for Hypothesis H4, confirming that customer engagement—across cognitive, emotional, and behavioral dimensions—is a significant predictor of repurchase intention on Xiaohongshu. Cognitive engagement fosters trust in product knowledge and decision-making. Emotional engagement nurtures brand attachment and affective loyalty. Behavioral engagement builds habitual usage and transactional ease. Together, these dimensions form a robust engagement-to-purchase pathway, validating the hypothesis that engagement is the foundation of sustainable repurchase behavior on digital platforms.

4.2.7. The Influence of Customer Engagement on eWOM (H5)

The fifth theme emerging from the qualitative interviews underscores the connection between customer engagement and users' willingness to engage in electronic word-of-mouth (eWOM) behaviors on Xiaohongshu. This hypothesis (H5) was quantitatively supported with a statistically significant, though relatively modest, path coefficient ($\beta = 0.098$, $p = .048$). The interview data provided rich contextual insights into how and why engaged users are more likely to share, recommend, or endorse content and products on the platform. Emotional satisfaction, cognitive confidence, and habitual participation were all described as triggers for eWOM behaviors, confirming that the engagement-to-advocacy pathway is both active and complex.

Participants indicated that when they felt informed and confident in their understanding of a topic—whether it was product use, service experience, or lifestyle advice—they were more inclined to share their perspectives. Users who had spent time reading, evaluating, and mentally processing content felt a sense of authority and responsibility to contribute back to the community.

"If I've done my research, tried the product, and it worked, I'll definitely share a review. I know how much I rely on others' posts, so I feel it's fair to give back."

(Participant 2, Female, 25 years old)

This illustrates that cognitive engagement cultivates a knowledge-sharing culture, where users are driven not only by personal experience but also by the cognitive investment they've made in learning

DOI: 10.55214/25768484.v9i6.8406

through the platform. The more users internalize content, the more likely they are to externalize it through eWOM activities like reviews, tutorial posts, or product comparisons.

"I wrote a post once breaking down different sunscreens because I had tried them all. I spent days reading reviews, so when I found what worked, I thought it could help others."

(Participant 11, Male, 33 years old)

The qualitative data also strongly supported the idea that emotional engagement is a key motivator of eWOM, particularly when users feel excited, grateful, or inspired by their experience on Xiaohongshu. Participants often described sharing content out of emotional satisfaction, especially after finding solutions to personal problems or connecting with inspiring stories.

"I recommended a brand of vegan makeup after reading an honest post. When I tried it and loved it, I felt so happy that I immediately posted my experience and tagged the original user."

(Participant 7, Female, 29 years old)

eWOM functions as an emotionally gratifying action—a way to both express appreciation and pass on a positive experience. Emotional resonance amplifies the desire to share, particularly when users feel part of a like-minded community. In this sense, Xiaohongshu becomes not just a commerce or review platform, but a social space where emotional engagement leads to brand or experience endorsement.

Users also shared that emotionally meaningful content—posts that made them feel inspired, reassured, or empowered—motivated them to repost, comment, or engage in storytelling of their own:

"There was a post about someone's weight-loss journey that made me cry. I shared it not just because it was useful, but because it moved me."

(Participant 5, Female, 24 years old)

Participants who were behaviorally engaged—those who used the platform regularly, commented often, and participated in challenges or trends—were naturally more inclined to share content and make recommendations. For these users, eWOM behavior was often a built-in feature of their routine, requiring no special prompting.

"I post weekly about products I try. It's become my habit, and I love when people ask questions or thank me. That interaction keeps me going." (Participant 15, Female, 27 years old)

This kind of routine-driven eWOM was especially prevalent among users who considered themselves micro-influencers or topic specialists within specific niches (e.g., skincare, parenting, minimalism). Behavioral engagement thus serves as a platform for personal expression and social validation, both of which encourage regular sharing and content contribution.

Moreover, the gamification features of Xiaohongshu—likes, saves, follower counts, and sharing metrics—serve as behavioral nudges that reinforce eWOM:

"When a post of mine gets shared or saved a lot, it's a signal that I should keep posting. It motivates me to share more, especially if I feel my content helps people."

(Participant 9, Male, 30 years old)

These insights confirm that habitual behavior and engagement frequency enhance users' willingness to act as brand ambassadors and content curators.

The qualitative analysis confirms Hypothesis H5, revealing that customer engagement is a significant antecedent of eWOM behavior on Xiaohongshu. Cognitive engagement leads to informed sharing rooted in trust and perceived expertise. Emotional engagement triggers affect-driven advocacy, where users share based on gratitude, excitement, or inspiration. Behavioral engagement fosters habitual sharing and content creation, reinforced by gamification and community validation. Together, these findings illustrate that engaged users are not only loyal consumers but also powerful promotors, contributing to the organic growth and reputation of the platform.

5. Discussions

The findings from this study offer substantial alignment with and extensions to prior research across multiple scholarly domains, including digital consumer engagement, social commerce, and information systems. Through the lens of the Stimulus–Organism–Response (SOR) framework, this research builds a comprehensive bridge between theoretical constructs and user experience on platforms like Xiaohongshu. The integration of quantitative data and qualitative narratives provides a multidimensional understanding of how user engagement is activated and transformed into behavioral outcomes such as repurchase and eWOM.

This study reinforces the utility and adaptability of the SOR model as originally proposed by Mehrabian and Russell [7] and as extended by later scholars in digital contexts [29]. The traditional application of the model posits that environmental stimuli influence internal psychological states (organism), which subsequently lead to behavioral responses. In this study, stimuli such as social interaction, information quality, and perceived value activate the organismic state of customer engagement, which in turn predicts repurchase and advocacy behavior.

These results align with recent research that has successfully applied the SOR model in online shopping and app usage contexts [30] affirming that the emotional and cognitive states of users serve as critical mediators between environmental design and commercial outcomes. This study contributes to that body of work by providing a granular understanding of the engagement dimensions and reinforcing the model's relevance in complex digital ecosystems.

The study extends foundational theories of engagement developed by Brodie, et al. [31]; Hollebeek, et al. [24] and Vivek, et al. [32] who conceptualize engagement as a psychological state comprising attention, absorption, and activation. Whereas these frameworks have emphasized the presence of engagement in general consumer contexts, this research differentiates engagement into cognitive, emotional, and behavioral components and reveals how each dimension is independently activated by specific stimuli.

For example, this study shows that cognitive engagement is most strongly influenced by information quality and perceived functional value, while emotional engagement is largely driven by emotional value and social interaction. These findings not only confirm the multidimensionality of engagement but also suggest stimulus-specific pathways to user involvement, providing actionable theoretical insight for future engagement modeling.

This specificity builds upon and nuances earlier studies that treated engagement as a latent aggregate construct, encouraging future scholars to consider contextual differences in engagement formation.

Consistent with the value theory in consumer research Kim, et al. [33] the findings of this study reinforce that perceived value—especially emotional and functional—plays a central role in driving user engagement and loyalty behaviors. However, unlike many earlier works that focused solely on economic or utilitarian value, this research shows that emotional value is an even more powerful driver of engagement in community-centered platforms.

These results align with recent literature on hedonic consumption and experiential value while expanding their relevance to digital communities. Moreover, this study contributes to the evolving understanding of reciprocal value creation in user-generated platforms, confirming that users are not passive consumers but co-creators who derive meaning from their contribution and connection to others [13].

Within the domain of social commerce, this study offers novel insight into how engagement leads to eWOM behavior, an area that has gained increased attention in recent years [3]. Previous studies have identified the importance of trust and community features in motivating eWOM, but few have explored the engagement-to-eWOM pathway through the lens of the SOR model.

This research contributes to filling that gap by showing that mentally attentive, emotionally satisfied, and behaviorally involved users are significantly more likely to recommend, share, and advocate for the platform and its associated brands. The qualitative findings further reveal that this behavior is not solely rational or incentivized—it is often emotionally reciprocal and socially motivated, a nuance underexplored in past work.

The findings thus expand on prior studies by offering a behavioral logic grounded in user psychology, confirming that eWOM is a natural byproduct of authentic and sustained engagement, not just a result of marketing strategy or monetary incentives.

6. Implications

6.1. Theoretical Implications

This study offers several key theoretical contributions, particularly in consumer behavior, digital engagement, and social commerce. By applying the Stimulus–Organism–Response (SOR) framework to the context of Xiaohongshu, the research advances theoretical understanding in three fundamental ways: it deepens the multidimensional interpretation of engagement, validates the extended SOR structure in a digital community, and highlights the role of perceived value in shaping sustained behavioral outcomes.

The first significant theoretical contribution is successfully extending the SOR model into the social commerce domain. Traditional applications of the SOR framework have typically emphasized linear pathways, often constrained to retail or website usability contexts [7]. This study, however, adapts the model to a dynamic digital ecosystem—Xiaohongshu—where stimuli go beyond environmental cues and include social, informational, and perceived value components.

This insight encourages scholars to move beyond aggregate engagement models and investigate how specific platform features or environmental conditions trigger unique engagement profiles—a perspective that could lead to more nuanced theoretical frameworks.

A further theoretical insight pertains to the critical role of perceived value in online community behavior. While value has often been considered in consumer behavior literature, its role in digital engagement is underexplored. This study reveals that economic, functional, and emotional values are pivotal for sustaining user interaction, platform loyalty, and community-based advocacy.

6.2. Practical Implications

One of the clearest takeaways for practitioners is the need to build robust social infrastructure into digital commerce platforms. The findings demonstrate that interactive features such as comment threads, real-time responses, collaborative content creation, and user support networks significantly enhance customer engagement.

For platforms like Xiaohongshu, this means investing in interface designs and algorithms prioritizing social visibility and personalized community experiences. For instance, promoting peer replies, featuring trending discussions, and highlighting user stories can amplify emotional and behavioral engagement.

Retailers within these platforms should encourage customers to leave detailed reviews, host Q&A discussions, or share user-generated tutorials. Such strategies drive purchase decisions and embed users deeper into the platform's social ecosystem.

While social visibility is essential, this study shows that information quality is even more critical to user trust, engagement, and retention. Marketers and content creators must ensure that their contributions are accurate, timely, and relevant to the specific needs of Xiaohongshu's user base.

For brand managers, this means crafting content that balances product promotion with educational or experiential value. Posts that include detailed explanations, authentic comparisons, and personalized narratives are more likely to engage users cognitively and emotionally.

Moreover, platforms can enhance content quality by incorporating fact-checking tools, user credibility scores, or expert endorsements, thereby increasing the perceived trustworthiness of information.

7. Future Study

Given the relatively modest strength of the path from customer engagement to electronic word-of-mouth (eWOM), future studies should seek to deepen the understanding of what motivates users to engage in eWOM behaviors. While this study confirmed that engagement leads to eWOM, it remains unclear why some highly engaged users actively share recommendations while others remain silent. Qualitative research focusing on the psychological, social, or identity-based motivations for eWOM could uncover the emotional, altruistic, or self-expressive reasons that drive users to become brand advocates.

It is equally important to explore the role of negative stimuli and disengagement dynamics, which were beyond the scope of the current study. While this research focused on positive platform experiences, future inquiries should examine how negative emotions, dissatisfaction, or platform fatigue influence disengagement. Understanding what causes users to reduce their activity or abandon a platform can provide a more balanced view of the engagement lifecycle and help platforms address retention challenges before they escalate.

As digital environments become increasingly intelligent, another promising direction for future research involves integrating artificial intelligence (AI) and personalization technologies as potential stimuli within the SOR framework. Emerging features such as AI-generated product recommendations, virtual shopping assistants, or algorithmically curated feeds significantly shape the user experience. Investigating how these personalized, machine-driven interactions influence cognitive, emotional, and behavioral engagement can shed light on the evolving role of automation in consumer-platform relationships.

Finally, considering Xiaohongshu's reliance on influencer-driven content, it would be valuable to examine how specific influencer characteristics—such as authenticity, expertise, and follower similarity—affect user engagement. Future studies might analyze whether different types of influencers (e.g., celebrities vs. micro-influencers) stimulate different engagement responses or whether particular follower–influencer dynamics foster stronger trust, higher repurchase rates, and more active eWOM participation.

Institutional Review Board Statement:

The study was conducted following the Declaration of Helsinki and approved by the Institutional Review Board of Suan Sunandha Rajabhat University.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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