

### Analyzing Key Factors of User Knowledge Sharing Intention and Its Impact in Beauty Online Communities: A Case Study on an Indonesia Beauty Platform

Christianto Vinsen Budijanto<sup>1\*</sup>, Shella Maria V.<sup>2</sup>, Dana Indra Sensuse<sup>3</sup>, Nadya Safitri<sup>4</sup>, Damayanti Elisabeth<sup>5</sup> <sup>1,2,3,4,5</sup>Fakultas Ilmu Komputer, Universitas Indonesia, Indonesia E-mail: <sup>1</sup>christianto.vinsen@ui.ac.id

### Abstract

This study investigates the factors influencing user knowledge-sharing intention and its impact in one of the biggest beauty online communities in Indonesia, by analyzing data from 113 respondents using Structural Equation Modeling (SEM). This study identifies perceived usefulness of shared knowledge, recognition, and reward systems as the top three key factors driving knowledge-sharing behavior. Findings reveal that usefulness of shared knowledge (path coefficient = 0.188, p = 0.012), recognition (path coefficient = 0.292, p = 0.001), and reward systems (path coefficient = 0.493, p = 0.000) significantly sustain participation by addressing intrinsic and extrinsic motivations. Barriers such as declining user engagement, technological limitations, and trust deficits were also examined, emphasizing the need for strategic interventions. Practical strategies, including enhanced gamification, targeted rewards, and visible recognition mechanisms, are proposed to foster continuous engagement and community growth.

*Keywords: beauty community, beauty platform, digital community, impacts, knowledge management, knowledge sharing* 

### **1. Introduction**

In the era of digital transformation, online communities have emerged as pivotal platforms for individuals to exchange knowledge on various subjects, including beauty [1]. One prominent example is one of the biggest online beauty platforms in Indonesia, where users actively share insights on beauty products, techniques, and industry trends. As the global beauty market evolves, the significance of these communities extends beyond personal interest to influencing consumer behavior and brand strategies [2]. Knowledge sharing within such platforms is a key component that fosters collaboration [3], innovation [4], and a sense of community among participants [5].

The phenomenon of knowledge sharing in digital beauty communities presents a unique set of characteristics, distinguishing it from traditional knowledge management frameworks seen in organizations [1]. Unlike structured corporate environments, participation in these communities is often voluntary and driven by intrinsic motivations such as personal interest or extrinsic rewards like recognition and influence [6]. Understanding the factors that motivate individuals to share knowledge, and the impact of such sharing is crucial for community managers, marketers, and researchers seeking to enhance user engagement and value creation.

Existing research on knowledge management highlights factors such as trust [7], social capital [8], and motivation as key drivers of knowledge sharing [6]. However, in this platform, the interplay of these factors is influenced by the dynamic nature of beauty trends and the open-access structure of the platform. A systematic review of literature (SLR) combined with a case study approach provides a comprehensive lens through which to explore these dynamics. Such an analysis not only identifies key enablers and barriers to knowledge sharing but also sheds light on the sustaining factors that maintain high levels of participation over time.



Sustained knowledge sharing on the platform is primarily hindered by motivational issues, including a lack of extrinsic rewards and declining intrinsic motivation due to burnout [9], as well as fear of negative feedback [10]. These challenges are worsened by technological shortcomings like inadequate features and lack of gamification, along with social barriers such as low trust, competitiveness, and free-riding [11]. Concerns over content quality and personal constraints—like time demands and self-doubt—further reduce engagement [11][12]. Addressing these motivational barriers is key to fostering continued participation. Table 1 presents our analysis of the platform, based on an interview with the Head of Product.

Table 1. Gap Analysis						
Expectation	Reality	Problem				
The activity of viewing product reviews and content knowledge increases by 20% each year.	The activity of viewing product review knowledge has decreased by 28.5%, and the activity of viewing other content knowledge has decreased by 26.5% (2024).	Knowledge-sharing and content-viewing activities in the platform show a declining trend in 2024.				
The activity of writing product reviews and content knowledge increases by 10% each year.	The activity of writing product review knowledge has decreased by 14.7%, and the activity of writing other content knowledge has decreased by 57% (2024).					
Knowledge-sharing activities on FD Talk can meet the average monthly activity target.	The average monthly knowledge- sharing activity on FD Talk in 2024 has not yet reached the company's target, achieving only 49% of the monthly average target.					

Based on the gap analysis, this paper seeks to answer two central research questions to overcome the problem:

**RQ1:** What are the key factors that sustain individual participation in knowledge sharing within the online community platform?

**RQ2:** What strategies can be implemented to enhance knowledge sharing in this platform?

The research contributes to a deeper understanding of the mechanisms driving knowledge sharing in digital beauty communities. It also offers practical insights for enhancing community engagement and knowledge management practices, thereby supporting the continued growth and sustainability of these vibrant online ecosystems.

### 2. Research Methodology

### 2.1. Indonesian Beauty Online Community Platforms

Indonesia has seen rapid growth in digital beauty communities, with numerous online platforms emerging to serve beauty enthusiasts across the country. These platforms provide dedicated spaces for users to share product reviews, beauty tips, skincare routines, and engage in discussions related to beauty and wellness [13]. In this study, we focus on one of the largest and most active beauty community platforms in Indonesia as a case study. The platform features a comprehensive product review system that allows users to write and browse thousands of detailed reviews on a wide range of beauty products [13]. Additionally, it offers an interactive forum where members discuss trends, techniques, and personal experiences—fostering a vibrant and supportive environment. With its large user base and emphasis on user-generated content, the platform exemplifies how digital communities can influence consumer behavior and encourage continuous knowledge sharing in the beauty sector [13].

# 2.2. Knowledge Sharing

Knowledge sharing (KS) is a crucial component of the knowledge management process, which includes stages such as knowledge discovery, capture, sharing, and application . KS plays a significant role within the knowledge management framework, involving individuals, teams, and organizations exchanging knowledge through various means [14]. Implementing KS in organizations brings numerous advantages, such as enhancing performance, improving productivity, and fostering long-term competitiveness [15]. This study will focus on KS activities facilitated by technology, often referred to as a knowledge sharing system.

Recent research continues to underscore the multifaceted nature of knowledge sharing, emphasizing the interplay between individual, organizational, and technological factors. A bibliometric analysis by Fauzi et al. highlights the enduring relevance of the Theory of Planned Behavior (TPB) in understanding KS behaviors, suggesting that integrating TPB with other theories can offer deeper insights into knowledge-sharing dynamics [16]. Furthermore, a systematic review by Anand and Dumazert identifies current themes in KS research, emphasizing the importance of organizational culture and technological infrastructure in facilitating effective knowledge exchange [17]. These studies collectively suggest that successful implementation of KS systems requires a holistic approach that considers behavioral intentions, organizational context, and technological support.

### 2.3. Related Works

The first paper investigates the factors influencing online knowledge sharing and its impact on the academic performance of academics at the University of Mosul, Iraq [18]. Using data from 211 respondents collected via electronic questionnaires, the researchers employed structural equation modeling with AMOS 24 software to analyze the relationships. The findings indicate that collaboration, perceived flexibility, and willingness to share significantly influence online knowledge sharing behavior, which in turn enhances academic performance. However, knowledge self-efficacy and communication were found to have no effect on online knowledge sharing behavior. The study highlights the importance of fostering collaboration and creating online groups for joint research through platforms like social media and dedicated scientific portals. While focusing on public university academics, the study suggests future research on personal characteristics and expanding the scope to medical professionals in hospitals. This research addresses a gap in existing literature by emphasizing online knowledge sharing in academia and its role in improving academic outcomes in contexts like Asia and Africa.

The second paper examines the impact of information technology (IT) and social networks on knowledge sharing and its subsequent effect on organizational performance at Lembaga Kantor Berita Nasional Antara (LKBN Antara), a state-owned enterprise (SOE) in Indonesia that implements knowledge management as part of the Making Indonesia 4.0 initiative [19]. Using structural equation modeling (SEM-PLS) and structured questionnaires distributed among employees, the findings reveal that social networks positively influence knowledge sharing, which in turn enhances organizational performance. However, the influence of IT on knowledge sharing was found to be weak. These results highlight the importance of fostering strong social networks within organizations to drive effective knowledge sharing and improve overall performance, while also indicating that IT's role in this context requires further exploration or enhancement.

The third paper investigates how experts' free knowledge sharing in online health communities (OHCs) impacts consumer engagement, both transactional and non-transactional, through the lens of social exchange theory [20]. Using homepage data from 2,982 experts on Haodf.com and employing negative binomial regression models, the findings reveal that both general and specific knowledge sharing positively influence consumer engagement. However, the study uncovers a trade-off, as higher knowledge-

sharing quality weakens the positive effects of knowledge-sharing quantity on engagement. These insights highlight the dual importance of quantity and quality in experts' contributions and provide guidance for OHC managers to refine knowledgesharing strategies, encouraging voluntary expert participation and improving the efficiency of healthcare information dissemination.

Extensive research consistently highlights the critical role of knowledge sharing across various sectors and contexts. In healthcare, it mediates the impact of AI on productivity by enhancing employee well-being, showing how technology benefits are realized through human collaboration [21]. In higher education, individual motivation—such as reputation—and social media tools like document sharing and virtual interaction significantly promote knowledge exchange and improve learning outcomes [22]. Similarly, shared leadership within teams enhances project success both directly and indirectly through improved cohesion and knowledge flow [23]. A systematic review also confirms that self-efficacy strongly influences individuals' willingness to share knowledge [24]. In supply chain networks, knowledge sharing acts as a partial mediator between collaborative innovation and firm performance, demonstrating its strategic value in inter-organizational cooperation [25]. Together, these studies underscore knowledge sharing's essential function in driving individual, team, and organizational success, forming a strong foundation for the present study.

### 2.4. Hypotheses

### 1. Individual Factors and Knowledge Sharing Intention

Individual factors play a crucial role in shaping knowledge-sharing behavior in online communities, as they are directly tied to the motivations and attitudes of users. Personal satisfaction, for instance, is one of the intrinsic factors that drive individuals to participate actively in knowledge sharing [26]. Research has shown that when individuals gain personal fulfillment from helping others, they are more likely to engage in sharing valuable information within a community. Similarly, recognition within the community further reinforces this behavior by providing external validation of one's contributions, leading to a stronger intention to share knowledge [27]. As individuals perceive recognition for their efforts, it encourages them to continue contributing. Based on those literature, we proposed that,

### H1a: Personal Satisfaction Is Positively Related to User Knowledge Sharing Intention in Beauty Online Communities

This hypothesis posits that individuals are more likely to share their knowledge in beauty online communities if they derive personal satisfaction from the act of sharing. Personal satisfaction could include feelings of accomplishment, enjoyment, or the fulfillment of helping others. When users feel good about their contributions, they are more inclined to continue sharing and participating, enhancing the overall knowledgesharing behavior within the community.

### H1b: Recognition Is Positively Related to User Knowledge Sharing Intention in Beauty Online Communities

Recognition, such as acknowledgment from peers or community leaders, can act as a powerful motivator for knowledge sharing [27]. This hypothesis suggests that when users receive recognition for their contributions—whether through praise, badges, or higher status—they are more likely to engage in knowledge-sharing activities. Recognition reinforces positive behavior and encourages users to continue sharing valuable insights and experiences in the community [28].

### 2. Community Factors and Knowledge Sharing Intention

Community factors are essential in facilitating knowledge sharing, as they highlight the importance of social dynamics and interpersonal relationships in online environments. Trust among members is foundational to creating a safe space for sharing information, as



users are more likely to engage when they feel that their contributions will be valued and respected [29]. Additionally, social capital—referring to the networks and relationships within the community—plays a significant role in fostering a sense of belonging and motivation to share knowledge [30]. A community with strong social ties encourages collaboration and the free flow of information, making members more willing to share. Based on these literature, we proposed that,

### H2a: Trust Is Positively Related to User Knowledge Sharing Intention in Beauty Online Communities

Trust among community members is crucial for fostering a knowledge-sharing environment [31]. This hypothesis argues that users are more willing to share knowledge in beauty online communities when they trust other members to value and use the shared information appropriately. High levels of trust reduce perceived risks associated with sharing personal or sensitive information and encourage more active participation [27].

### H2b: Social Capital Is Positively Related to User Knowledge Sharing Intention in Beauty Online Communities

Social capital, referring to the networks and relationships within a community, plays a key role in enhancing knowledge-sharing intentions [32]. This hypothesis suggests that users with strong social ties or a sense of belonging within the community are more likely to engage in knowledge sharing. The more connected users feel to the community, the more they are motivated to contribute and help others [33].

#### 3. Technology Factors and Knowledge Sharing Intention

Technology factors are integral to shaping the experience of users in online communities, as they provide the tools and platforms that enable knowledge sharing. A user-friendly platform enhances the likelihood of participation, as users are more inclined to share when the platform is easy to navigate and facilitates communication effectively [26]. Furthermore, reward systems that incentivize users to contribute their knowledge have been found to increase knowledge-sharing behaviors [34]. These technological features not only improve user experience but also create an environment where sharing knowledge becomes an enjoyable and rewarding activity. Based on those literature, we proposed that,

### H3a: Platform Usability Is Positively Related to User Knowledge Sharing Intention in Beauty Online Communities

This hypothesis highlights the importance of a user-friendly platform in promoting knowledge sharing. If the beauty online community platform is easy to navigate, intuitive, and accessible, users are more likely to engage in knowledge-sharing activities [26]. A seamless user experience reduces barriers to participation and encourages users to share their knowledge more frequently and effectively [35].

### H3b: Reward System Is Positively Related to User Knowledge Sharing Intention in Beauty Online Communities

A reward system can serve as an incentive for users to share their knowledge within a beauty online community [29]. This hypothesis suggests that when users are provided with tangible or intangible rewards—such as points, badges, or recognition—they are more motivated to contribute valuable information. The reward system helps reinforce knowledge-sharing behavior by making users feel valued for their contributions [32].

#### 4. Knowledge Factors and Knowledge Sharing Intention

Knowledge factors directly influence users' willingness to share their expertise and insights within an online community. Perceived quality of information is key, as users are more likely to share when they believe their knowledge is of high value to the community [29]. Additionally, the usefulness of shared knowledge plays a significant role in encouraging contributions, as users are motivated to share information that they believe will be practically beneficial to others. When users perceive the shared knowledge as



useful, it reinforces the value of their contributions and encourages continuous participation. Based on those literature, we proposed that,

# H4a: Perceived Quality Is Positively Related to User Knowledge Sharing Intention in Beauty Online Communities

Perceived quality refers to the value and relevance of the information shared within the community [27]. This hypothesis suggests that users are more likely to engage in knowledge sharing when they perceive that the shared knowledge is high in quality. When users see that others are providing valuable, credible, and useful information, they are more motivated to contribute their own knowledge to maintain the community's standards [29].

## H4b: Usefulness of Shared Knowledge Is Positively Related to User Knowledge Sharing Intention in Beauty Online Communities

This hypothesis emphasizes the practical utility of shared knowledge. If users perceive the knowledge shared within a beauty online community as useful or beneficial to their own needs or the needs of others, they are more likely to engage in sharing their own knowledge [32]. The usefulness of shared knowledge creates a cycle of continuous knowledge exchange, motivating users to contribute their insights for the benefit of the community.

### 5. The Impact of User Knowledge Sharing Intention

Knowledge sharing in online communities not only impacts the community itself but also has significant benefits for individual users. User satisfaction is one of the most important outcomes of knowledge sharing, as individuals who contribute to the community often experience positive emotional and cognitive rewards [31]. By actively sharing their knowledge, users gain a sense of accomplishment and connection, which enhances their overall satisfaction [26]. In addition, the act of sharing knowledge can contribute to personal growth, as individuals deepen their own understanding, improve their skills, and gain new perspectives through engagement with others [28]. Moreover, knowledge sharing can foster stronger brand loyalty, as users who feel valued and involved are more likely to develop an emotional attachment to the brands and communities they engage with [36]. This emotional connection can lead to increased long-term loyalty and advocacy for the brand. Based on those literature, we proposed that, H5: User Knowledge Sharing Intention Is Positively Related to User Satisfaction H6: User Knowledge Sharing Intention Is Positively Related to Personal Growth H7: User Knowledge Sharing Intention Is Positively Related to Enhanced Brand Loyalty



Figure 1. Research Model

### KESATRIA: Jurnal Penerapan Sistem Informasi (Komputer & Manajemen) Terakreditasi Nomor 204/E/KPT/2022 | Vol. 6, No. 2, April (2025), pp. 521-536

### 2.5. Data Collection

This study employed a quantitative approach, utilizing an online survey method to collect data through a structured questionnaire. The questionnaire was designed to evaluate the factors that sustain knowledge-sharing behavior within this platform. Before distribution, the questionnaire underwent a readability test to ensure the clarity and comprehensibility of the questions. The readability test aimed to confirm that respondents could easily interpret and respond to each question using the provided five-point Likert scale, where "1" indicates strong disagreement and "5" represents strong agreement.

The target respondents were members of this platform who had participated in at least one form of interaction within the community, such as posting, commenting, or sharing knowledge. A random sampling technique was employed to select participants, ensuring diversity in responses. Data collection was conducted over a four-day period from December 11 to December 14, 2024. A total of 113 responses were deemed valid for analysis after data cleaning. The demographic profile of the respondents is summarized in Table 2.

Characteristics	Item	Frequency
Age	18 and Under	11
	19 – 24	40
	25 - 29	31
	30 - 34	17
	35+	14
Gender	Female	84
	Male	17
	Prefer not to say	12
Joined Community Since	Less than 6 months	11
	6-12 months	17
	1-3 years	40
	More than 3 years	45
Frequent Engagement in the Community	Daily	30
	Weekly	64
	Monthly	10
	Rarely	9

Table 2. The Sample Characteristics

#### 2.6. Data Analysis

The collected data were analyzed using Structural Equation Modeling (SEM) through the SmartPLS software version 4.1.0.9. This advanced analytical technique was chosen due to its ability to simultaneously assess the relationships between latent variables and evaluate complex models with multiple hypotheses. SEM was particularly appropriate for testing the relationships hypothesized in the conceptual model, as illustrated in Figure 1.

The first stage involved the measurement model analysis to validate the reliability and validity of the constructs. Internal consistency was assessed using Cronbach's Alpha with a threshold value greater than 0.60, and Composite Reliability (CR) with a threshold value greater than 0.70. Convergent validity was evaluated using the Average Variance Extracted (AVE), with values exceeding 0.50 indicating sufficient convergence. Discriminant validity was verified using the Fornell-Larcker Criterion to ensure that each construct was distinct from others. The second stage focused on the structural model analysis to test the hypothesized relationships. Path coefficients ( $\beta$ ) were assessed, and their significance was tested using a bootstrapping technique with 5,000 subsamples. This stage aimed to determine the strength and significance of the relationships between the constructs in the model, providing insights into the underlying dynamics of the study.



KESATRIA: Jurnal Penerapan Sistem Informasi (Komputer & Manajemen) Terakreditasi Nomor 204/E/KPT/2022 | Vol. 6, No. 2, April (2025), pp. 521-536

### 3. Results & Discussions

#### **.** 3.1. Measurement Model Evaluation

The measurement model evaluation was conducted to ensure the reliability and validity of the constructs, focusing on eight key factors: Personal Satisfaction (PS), Recognition (R), Trust (T), Social Capital (SC), Platform Usability (PU), Reward System (RS), Perceived Quality (PQ), and Usefulness of Shared Knowledge (USK). Each construct was assessed for indicator reliability, construct reliability, convergent validity, and discriminant validity.

Construct	CA	CR	AVE
PS	-0.009	0.009	0.502
R	0.765	0.785	0.808
Т	0.181	-0.432	0.480
SC	0.222	-0.294	0.440
PU	0.176	0.568	0.520
RS	0.283	0.285	0.582
PQ	-0.039	-0.138	0.497
USK	0.746	0.756	0.797

 Table 3. Constructs Reliability And Availability

Note: CA: Cronbach's Alpha: CR: composite reliability: AVE: average variance extracted: PO: Perceived Quality: PS: Personal Satisfaction: PU: Platform Usability; R: Recognition; RS: Reward System; SC: Social Capital; T: Trust; US: User Satisfaction; USK: Usefulness of Shared Knowledge

Table 3 summarizes the results of the reliability and validity assessment for the constructs in the research model, including Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE). For Recognition (R) and Usefulness of Shared Knowledge (USK), the constructs demonstrate strong reliability and validity, with CA values of 0.765 and 0.746, CR values of 0.785 and 0.756, and AVE values above the recommended threshold of 0.5, at 0.808 and 0.797 respectively. Reward System (RS) also meets the reliability and validity criteria, with an AVE of 0.582 and moderate CA and CR values. However, other constructs, including Personal Satisfaction (PS), Trust (T), Social Capital (SC), and Perceived Quality (PQ), show slightly lower CA and CR values, with AVE values near or slightly below the threshold. This outcome may reflect the subjective and multi-dimensional nature of these constructs, which can vary significantly depending on individual interpretation. In addition, the demographic profile of respondents—who predominantly consist of young adults actively engaging in beautyrelated discussions-could influence how certain constructs are perceived and valued. For example, constructs like trust or social capital may not yet be fully developed or prioritized in this community, especially when interactions are brief and centered around product recommendations. Furthermore, the situational context of the research setting, which emphasizes informal peer-to-peer interactions, may also affect the strength of certain constructs that are typically more prominent in formal or structured communities. These findings offer useful insight into how the unique characteristics of respondents and the platform environment shape the measurement outcomes. While several constructs meet the expected standards, these observations provide an opportunity for thoughtful refinement and contextual adjustment in future studies.

Item	Outer Loading	Mean	SD	Validity
bPS1	0.809	2.522	0.951	1
PS2	-0.592	3.212	1.163	-
R1	0.919	4.398	0.793	1
R2	0.878	4.381	0.683	1
T1	0.967	4.053	0.861	1
T2	-0.158	2.991	1.244	-
SC1	-0.542	3.991	0.723	-

Table 4. Factor Loading

<b>e</b> sînta		KESATRIA: Jurn erakreditasi Nomor	al Penera 204/E/KP	pan Siste T/2022	em Informas Vol. 6, No. 2	i (Komputer & Manajemen) 2, April (2025), pp. 521-536
	Item	Outer Loading	Mean	SD	Validity	
	SC2	0.767	3.796	0.864	~	
	PU1	0.987	3.124	1.161	~	
	PU2	0.257	2.664	1.086	-	
	RS1	0.735	4.257	0.726	1	
	RS2	0.790	4.434	0.622	1	
	PQ1	0.123	3.823	0.989	-	
	PQ2	0.990	3.947	0.958	~	
	USK1	0.908	4.398	0.645	1	
	USK2	0.877	4.230	0.729	1	

Note: SD; standard deviation; PQ: Perceived Quality; PS: Personal Satisfaction; PU: Platform Usability; R: Recognition; RS: Reward System; SC: Social Capital; T: Trust; US: User Satisfaction; USK: Usefulness of Shared Knowledge.

Table 4 presents the factor loadings for the observed variables across eight constructs, evaluating their strength in representing the latent constructs. For Personal Satisfaction (PS), PS1 demonstrates strong reliability with a loading of 0.809, while PS2 falls below the recommended threshold with -0.592. The Recognition (R) construct is robustly represented by R1 (0.919) and R2 (0.878), indicating high reliability. Trust (T) is strongly supported by T1 (0.967), though T2 has a negative and weak loading of -0.158. For Social Capital (SC), SC2 shows moderate reliability with a loading of 0.767, whereas SC1 does not meet the threshold with -0.542. The Platform Usability (PU) construct is strongly represented by PU1 (0.987), but PU2 exhibits a weaker loading of 0.257. Reward System (RS) is well-supported by RS1 (0.735) and RS2 (0.790), both above the acceptable range. The Perceived Quality (PQ) construct is robustly validated by PQ2 (0.990), despite a low loading for PQ1 (0.123). Lastly, Usefulness of Shared Knowledge (USK) shows strong support with USK1 (0.908) and USK2 (0.877). Overall, while several indicators perform well, some constructs require further refinement to enhance measurement reliability.

1,000							100	be	-	00	UDIX
0,051	1,000										
0,027	0,025	1,000									
-0,045	0,209	-0,177	0,705								
-0,080	0,035	-0,051	-0,154	0,709							
-0,093	0,109	0,028	-0,029	-0,175	0,721						
-0,121	0,435	-0,038	0,164	0,102	0,036	0,899					
0,139	0,578	0,093	0,090	0,084	0,039	0,159	0,763				
0,169	-0,014	0,062	-0,047	0,031	-0,093	-0,114	0,117	0,664			
0,246	-0,108	0,027	0,016	0,130	-0,016	0,026	0,044	-0,142	0,693		
0,074	0,072	-0,127	-0,040	-0,055	0,165	0,015	-0,054	-0,219	-0,052	1,000	
-0,078	0,350	0,085	0,043	-0,120	0,141	0,212	0,180	-0,078	0,003	0,057	0,893
	0,027 -0,045 -0,080 -0,093 -0,121 0,139 0,169 0,246 0,074 -0,078 v: KSL K	0,027         0,025           0,045         0,209           -0,080         0,035           -0,093         0,109           -0,121         0,435           0,139         0,578           0,169         -0,014           0,246         -0,108           0,072         0,072           -0,078         0,350           v KSU Knowledge S	0.027         0.025         1,000           -0.045         0.209         -0,177           -0.080         0.035         -0.051           -0.093         0,109         0,028           -0,121         0,435         -0,038           0,139         0,578         0,093           0,169         -0,014         0,062           0,246         -0,108         0,027           0,074         0,072         -0,127           -0,074         0,350         0,085           v KSE Krowladea Shering Litzer         Versiter         Versiter	0,027         0,025         1,000           -0,045         0,209         -0,177         0,705           -0,080         0,035         -0,051         -0,154           -0,093         0,109         0,028         -0,029           -0,121         0,435         -0,038         0,164           0,139         0,578         0,093         0,090           0,169         -0,014         0,062         -0,047           0,246         -0,108         0,027         0,016           0,074         0,072         -0,127         -0,040           -0,035         0,085         0,043         0,043	0,027         0,025         1,000           -0,045         0,209         -0,177         0,705           -0,080         0,035         -0,051         -0,154         0,709           -0,093         0,109         0,028         -0,029         -0,175           -0,121         0,435         -0,038         0,164         0,102           0,139         0,578         0,093         0,090         0,084           0,169         -0,014         0,062         -0,047         0,031           0,246         -0,108         0,027         0,016         0,130           0,074         0,072         -0,127         -0,040         -0,055           -0,038         0,085         0,043         -0,120	0,027         0,025         1,000	0,027         0,025         1,000             -0,045         0,209         -0,177         0,705             -0,045         0,209         -0,177         0,705             -0,080         0,035         -0,051         -0,154         0,709             -0,093         0,109         0,028         -0,029         -0,175         0,721            -0,121         0,435         -0,038         0,164         0,102         0,036         0,899           0,139         0,578         0,093         0,090         0,084         0,039         0,159           0,169         -0,014         0,062         -0,047         0,031         -0,093         -0,114           0,246         -0,108         0,027         0,016         0,130         -0,016         0,026           0,074         0,072         -0,127         -0,040         -0,055         0,165         0,015           -0,078         0,350         0,085         0,043         -0,120         0,141         0,212           -0,078         0,350         0,085         0,043         -0,120         0,141	0,027         0,025         1,000              -0,045         0,209         -0,177         0,705              -0,045         0,209         -0,177         0,705              -0,080         0,035         -0,051         -0,154         0,709             -0,093         0,109         0,028         -0,029         -0,175         0,721            -0,121         0,435         -0,038         0,164         0,102         0,036         0,899           0,139         0,578         0,093         0,090         0,084         0,039         0,159         0,763           0,169         -0,014         0,062         -0,047         0,031         -0,093         -0,114         0,117           0,246         -0,108         0,027         0,016         0,130         -0,016         0,026         0,044           0,074         0,072         -0,127         -0,040         -0,055         0,165         0,015         -0,554           -0,078         0,350         0,085         0,043         -0,120         0,141         0,212	0,027         0,025         1,000              -0,045         0,209         -0,177         0,705              -0,045         0,209         -0,177         0,705              -0,080         0,035         -0,051         -0,154         0,709             -0,093         0,109         0,028         -0,029         -0,175         0,721             -0,121         0,435         -0,038         0,164         0,102         0,036         0,899            0,139         0,578         0,093         0,090         0,084         0,039         0,159         0,763           0,169         -0,014         0,062         -0,047         0,031         -0,093         -0,114         0,117         0,664           0,246         -0,108         0,027         0,016         0,130         -0,016         0,026         0,044         -0,142           0,074         0,072         -0,127         -0,040         -0,055         0,165         0,015         -0,054         -0,219           0,078         0,350         <	0,027         0,025         1,000                -0,045         0,209         -0,177         0,705	0,027         0,025         1,000  .

Table 5. Fornell-Larcker Criterion

Notes: BL: Brand Loyalty; KSI: Knowledge Sharing Intention; PG: Personal Growth; PQ: Perceived Quality; PS: Personal Satisfaction; PU: Platform Usability; F Recognition; RS: Reward System; SC: Social Capital; T: Trust; US: User Satisfaction; USK: Usefulness of Shared Knowledge

Table 5 presents the Fornell-Larcker Criterion, utilized to evaluate the discriminant validity of constructs within the research model. Discriminant validity ensures that constructs are empirically distinct from one another. The diagonal values represent the square root of the Average Variance Extracted (AVE) for each construct, while the off-diagonal values indicate correlations between constructs. For example, the constructs Recognition (R) and Usefulness of Shared Knowledge (USK) exhibit strong discriminant validity, with diagonal values of 0.899 and 0.893, respectively, exceeding their correlations with other constructs. Similarly, Reward System (RS), Perceived Quality (PQ), and Platform Usability (PU) demonstrate discriminant validity with diagonal values of 0.763, 0.705, and 0.721, respectively, surpassing their inter-construct correlations. However, some constructs, such as Trust (T) and Social Capital (SC), show relatively lower diagonal values (0.693 and 0.664), which, while adequate, may indicate weaker discriminant validity compared to other constructs. Overall, the results confirm that the



constructs meet the criteria for discriminant validity in most cases, ensuring their empirical distinction in the research model. 

### 3.2. Structural Model Evaluation

Figure 2 illustrates the structural model results from the PLS-SEM analysis, showcasing the relationships among the constructs: Personal Satisfaction (PS), Recognition (R), Trust (T), Social Capital (SC), Platform Usability (PU), Reward System (RS), Perceived Quality (PQ), Usefulness of Shared Knowledge (USK), User Knowledge Sharing Intention (KSI), Personal Growth (PG), and Brand Loyalty (BL). The numbers on the paths represent the standardized path coefficients, while the numbers in parentheses indicate the p-values for the statistical significance of these relationships.



### Figure 2. Analysis Result

Table 6 presents the R-Square and Adjusted R-Square values for the endogenous constructs in the research model, which reflect the explanatory power of the predictors. R-Square values indicate the proportion of variance in the dependent variables explained by the independent variables. R-Square values can be categorized as weak (0.19), moderate (0.33), and substantial (0.67).

	<b>R-square</b>	<b>R-square adjusted</b>			
BL	0.003	-0.006			
KSI	0.526	0.490			
PG	0.001	-0.008			
US	0.005	-0.004			

Table 6 Dath Coofficient

In this study, Brand Loyalty (BL) has an R-Square of 0.003, indicating that the predictors explain only 0.3% of its variance. The Adjusted R-Square value of -0.006 suggests that the model lacks explanatory power for this construct, categorizing it as weak.



Knowledge Sharing Intention (KSI) has an R-Square of 0.526, meaning that 52.6% of its variance is explained by its predictors, with an Adjusted R-Square of 0.490, reflecting a moderate to substantial level of explanatory power. Personal Growth (PG) has an R-Square of 0.001, suggesting that only 0.1% of its variance is explained by the model. The Adjusted R-Square value of 0.008 indicates negligible explanatory power, categorizing it as weak. Similarly, User Satisfaction (US) has an R-Square of 0.005, signifying that 0.5% of its variance is explained by the predictors, with an Adjusted R-Square of -0.004, further indicating a very weak relationship.

These results highlight that the model provides substantial explanatory power only for Knowledge Sharing Intention (KSI), while its ability to explain variance in Brand Loyalty (BL), Personal Growth (PG), and User Satisfaction (US) is limited. The Adjusted R-Square values, which account for the number of predictors, further emphasize the weak explanatory power for most constructs except KSI.

	Path coef.	T Statistics	P value	Status
KSI -> BL	0,051	0,563	0,574	-
KSI -> PG	0,025	0,281	0,779	-
KSI -> US	0,072	0,814	0,416	-
PQ -> KSI	0,116	1,410	0,159	-
PS -> KSI	0,035	0,409	0,683	-
PU -> KSI	0,057	0,640	0,522	-
R -> KSI	0,292	3,463	0,001	1
RS -> KSI	0,493	7,283	0,000	1
SC -> KSI	-0,034	0,423	0,672	-
T -> KSI	-0,148	1,284	0,199	-
USK -> KSI	0,188	2,513	0,012	1

**Table 7.** Path Coefficient Detailed

Notes: BL: Brand Loyalty; KSI: Knowledge Sharing Intention; PG: Personal Growth; PQ: Perceived Quality; PS: Personal Satisfaction; PU: Platform Usability; R: Recognition; RS: Reward System; SC: Social Capital; T: Trust; US: User Satisfaction; USK: Usefulness of Shared Knowledge.

Table 7 displays the path coefficients, T-statistics, and p-values obtained from the PLS-SEM analysis, which assess the magnitude, significance, and direction of the relationships between constructs in the research model. The path coefficients indicate the standardized strength of these relationships, while the T-statistics and p-values provide insights into their statistical significance. The result of the accepted constructs are:

- R → KSI (0.292, T=3.463, p=0.001): The relationship between Recognition (R) and Knowledge Sharing Intention (KSI) is significant, with a path coefficient of 0.292. This indicates that recognition positively and significantly influences users' intentions to share knowledge within the community.
- 2. RS  $\rightarrow$  KSI (0.493, T=7.283, p=0.000): Reward System (RS) has a strong and highly significant impact on Knowledge Sharing Intention (KSI), with a path coefficient of 0.493. This demonstrates that effective reward systems play a critical role in motivating users to share their knowledge.
- USK → KSI (0.188, T=2.513, p=0.012): The relationship between Usefulness of Shared Knowledge (USK) and Knowledge Sharing Intention (KSI) is significant, with a path coefficient of 0.188. This suggests that when shared knowledge is perceived as useful, users are more likely to engage in knowledge sharing.

These results confirm the significance of the hypothesized relationships in the research model, particularly the critical role of Recognition (R), Reward System (RS), and Usefulness of Shared Knowledge (USK) in driving Knowledge Sharing Intention (KSI), aligning with prior literature that emphasizes these factors as key drivers of engagement and collaboration in online beauty communities. These constructs appear to closely align with user motivations in this context, where appreciation, perceived value of contributions, and incentives are central to encouraging participation.



However, the relationships of Personal Satisfaction (PS), Trust (T), Social Capital (SC), Platform Usability (PU), and Perceived Quality (PQ) with Knowledge Sharing Intention (KSI), as well as the impact of KSI on Personal Growth (PG), Brand Loyalty (BL), and User Satisfaction (US), were not supported, suggesting that these variables may have a less direct influence in this specific setting. This result may be influenced by the demographic characteristics of the respondents, who are predominantly young adults engaged in fast-paced, topical discussions around beauty-related themes. In such communities, users may place higher emphasis on recognition and immediate value rather than on deeper relational or emotional constructs such as trust or long-term satisfaction.

In addition, the informal nature of interactions and the platform's community culture may lead users to prioritize quick, trend-driven exchanges over structured engagement or long-term loyalty. Constructs like Personal Growth, Brand Loyalty, and User Satisfaction may emerge more clearly over time through sustained and meaningful interactions, which might not be fully captured in the present cross-sectional analysis. These findings reflect the importance of context in evaluating knowledge sharing behavior and highlight opportunities for future research to explore potential moderating or temporal effects that could further explain the dynamics of user engagement in similar digital communities.

### **3.3. Strategies for The Platform**

After conducting a PLS-SEM analysis, it was found that the usefulness of shared knowledge, recognition, reward system are the most significant factors driving knowledge-sharing intentions within this platform. While usefulness of shared knowledge and recognitions are the two key factors in encouraging knowledge sharing, rewards system plays a pivotal value in sustaining participation to foster continuous engagement in beauty digital communities. Enhancing knowledge sharing in this platform requires a strategic optimization of the existing reward system, which includes badges like "bronze," "silver," "gold," and "platinum". This can be achieved by creating a more dynamic and engaging gamification framework that ties these rewards to specific knowledge-sharing milestones, such as writing a certain number of high-quality reviews or consistently participating in community discussions. To attract new users, promotional campaigns highlighting the benefits and achievements of top contributors could be introduced, emphasizing the prestige associated with higher-tier badges. For retaining current users, exclusive incentives such as early access to beauty trends, product samples, or personalized recognition events for top contributors can add tangible value to their engagement. Additionally, enhancing the visibility of these rewards within the platform, such as featuring top contributors prominently or introducing social sharing options for badge achievements, could foster a stronger sense of accomplishment and community recognition. These strategies collectively support sustained participation and enrich the overall user experience.

#### **3.4.** Theoretical Implication

This study enriches the theoretical understanding of knowledge-sharing behaviors in online communities, specifically within the context of digital beauty platforms. By integrating constructs such as recognition, reward systems, and the perceived usefulness of shared knowledge, the research advances knowledge management theories by highlighting the nuanced interplay of intrinsic and extrinsic motivators in voluntary, noncorporate settings. The findings extend the applicability of these theories beyond traditional organizational frameworks, emphasizing the role of dynamic, user-driven interactions in fostering knowledge exchange. Moreover, the significant influence of extrinsic motivators such as rewards and recognition on knowledge-sharing intentions suggests a critical reevaluation of the motivational constructs in online community research, advocating for a balance between intrinsic satisfaction and external incentives to sustain engagement.

### 3.5. Practical Implication

The insights from this study provide actionable strategies for community managers and marketers aiming to enhance user participation, and engagement in digital beauty communities like this platform. Implementing an optimized reward system that ties gamified achievements to tangible benefits—such as badges, exclusive perks, or early access to beauty products—can foster sustained, user engagement. Additionally, emphasizing the visibility and recognition of top contributors through social sharing features and platform-based accolades can strengthen users' sense of accomplishment and community belonging. These practical measures not only address declining trends in knowledge sharing but also create a more vibrant and collaborative community environment, ultimately benefiting both users and brands by promoting deeper engagement and loyalty.

### 4. Conclusion

This study on this platform provides a deeper understanding of the dynamics within beauty digital communities, where knowledge sharing significantly shapes user engagement and community vitality. The research highlights individual, community, technological, and knowledge-related factors as key drivers influencing knowledgesharing intentions. Individual factors, such as personal satisfaction and recognition, motivate users to actively participate, while trust and social capital within the community create a conducive environment for collaboration. Technological enablers, such as userfriendly platforms and robust reward systems, were found to be pivotal in sustaining participation. The perceived quality and usefulness of shared knowledge also significantly enhance users' willingness to contribute. Among these, the usefulness of shared knowledge (path coefficient = 0.188, p = 0.012), recognition (path coefficient = 0.292, p = 0.001), and reward systems (path coefficient = 0.493, p = 0.000) emerged as three main key factors in encouraging knowledge sharing, as they provide tangible and intangible incentives that resonate with users' intrinsic and extrinsic motivations. The importance of implementing effective reward mechanisms were found to be pivotal in sustaining participation to foster continuous engagement in beauty digital communities.

Future research should explore longitudinal studies to capture evolving user behaviors and preferences within beauty digital communities, where the dynamic nature of trends and innovations creates unique opportunities and challenges. Incorporating qualitative methods, such as in-depth interviews, could provide richer insights into individual motivations and barriers, particularly in contexts where personal identity and aesthetic expression are central. Advanced technologies, such as artificial intelligence and machine learning, could be leveraged to optimize platform usability, recommend personalized content, and improve the overall user experience. Expanding the study to include diverse beauty digital communities across different cultural and market contexts could validate the generalizability of the findings and uncover unique patterns. Finally, developing and testing targeted intervention strategies based on the identified factors—such as gamification features or tailored recognition mechanisms—could further enhance sustainable knowledge-sharing practices and foster stronger community cohesion in beauty-focused digital ecosystems.

### References

[1] J.-L. Chen and A. Dermawan, "The Influence of YouTube Beauty Vloggers on Indonesian Consumers' Purchase Intention of Local Cosmetic Products," *International Journal of Business and Management*, vol. 15, no. 5, p. 100, Apr. 2020, doi: 10.5539/ijbm.v15n5p100.

- [2] Z. R. Santos, C. M. K. Cheung, P. S. Coelho, and P. Rita, "Consumer engagement in social media brand communities: A literature review," *Int J Inf Manage*, vol. 63, p. 102457, Apr. 2022, doi: 10.1016/j.ijinfomgt.2021.102457.
- [3] M. H. Jarrahi, D. Askay, A. Eshraghi, and P. Smith, "Artificial intelligence and knowledge management." A partnership between human and AI," *Bus Horiz*, vol. 66, no. 1, pp. 87–99, Jan. 2023, doi: 10.1016/j.bushor.2022.03.002.
- [4] D. I. Castaneda and S. Cuellar, "Knowledge sharing and innovation: A systematic review," *Knowledge and Process Management*, vol. 27, no. 3, pp. 159–173, Jul. 2020, doi: 10.1002/kpm.1637.
- [5] R. Chatterjee and A.-P. Correia, "Online Students' Attitudes Toward Collaborative Learning and Sense of Community," *American Journal of Distance Education*, vol. 34, no. 1, pp. 53–68, Jan. 2020, doi: 10.1080/08923647.2020.1703479.
- [6] B. McAteer, W. Flannery, and B. Murtagh, "Linking the motivations and outcomes of volunteers to understand participation in marine community science," *Mar Policy*, vol. 124, p. 104375, Feb. 2021, doi: 10.1016/j.marpol.2020.104375.
- [7] R. Kmieciak, "Trust, knowledge sharing, and innovative work behavior: empirical evidence from Poland," *European Journal of Innovation Management*, vol. 24, no. 5, pp. 1832–1859, Oct. 2021, doi: 10.1108/EJIM-04-2020-0134.
- [8] R. Miković, D. Petrović, M. Mihić, V. Obradović, and M. Todorović, "The integration of social capital and knowledge management – The key challenge for international development and cooperation projects of nonprofit organizations," *International Journal of Project Management*, vol. 38, no. 8, pp. 515–533, Nov. 2020, doi: 10.1016/j.ijproman.2020.07.006.
- [9] S. Lombardi, V. Cavaliere, L. Giustiniano, and F. Cipollini, "What Money Cannot Buy: The Detrimental Effect of Rewards on Knowledge Sharing," *European Management Review*, vol. 17, no. 1, pp. 153–170, Mar. 2020, doi: 10.1111/emre.12346.
- [10] V. Pereira and M. Mohiya, "Share or hide? Investigating positive and negative employee intentions and organizational support in the context of knowledge sharing and hiding," *J Bus Res*, vol. 129, pp. 368–381, May 2021, doi: 10.1016/j.jbusres.2021.03.011.
- [11] A. Anand, P. Centobelli, and R. Cerchione, "Why should I share knowledge with others? A review-based framework on events leading to knowledge hiding," *Journal of Organizational Change Management*, vol. ahead-of-print, no. ahead-of-print, Apr. 2020, doi: 10.1108/JOCM-06-2019-0174.
- [12] M. J. S. P. Oliveira and P. Pinheiro, "Factors and Barriers to Tacit Knowledge Sharing in Non-Profit Organizations – a Case Study of Volunteer Firefighters in Portugal," *Journal of the Knowledge Economy*, vol. 12, no. 3, pp. 1294–1313, Sep. 2021, doi: 10.1007/s13132-020-00665-x.
- [13] https://femaledaily.com/about, "Female Daily Network," 2024.
- [14] K. M. Wiig, "What future knowledge management users may expect," Journal of Knowledge Management, vol. 3, no. 2, pp. 155–166, Apr. 1999, doi: 10.1108/13673279910275611.
- [15] X. Sun, R. Huang, Z. Jiang, J. Lu, and S. Yang, "On tacit knowledge management in product design: status, challenges, and trends," *Journal of Engineering Design*, pp. 1–38, Apr. 2024, doi: 10.1080/09544828.2023.2301232.
- [16] M. Á. López-Cabarcos, S. Srinivasan, and P. Vázquez-Rodríguez, "An approach to firm's innovation from the explicit and tacit knowledge spiral," *Knowledge Management Research & Practice*, vol. 22, no. 4, pp. 340–353, Apr. 2024, doi: 10.1080/14778238.2023.2173679.
- [17] I. Nonaka, "A Dynamic Theory of Organizational Knowledge Creation," *Organization Science*, vol. 5, no. 1, pp. 14–37, Apr. 1994, doi: 10.1287/orsc.5.1.14.

- [18] B. A. Alyouzbaky, M. Y. M. Al-Sabaawi, and A. Z. Tawfeeq, "Factors affecting online knowledge sharing and its effect on academic performance," VINE Journal of Information and Knowledge Management Systems, vol. 54, no. 5, pp. 990–1010, 2024.
- [19] E. G. Mirdhal, Y. Kurniawan, and S. Candra, "The Impact of Information Technology and Social Network in Knowledge Sharing for Organization Performance (A Case Study Approach)," in 2023 8th International Conference on Business and Industrial Research (ICBIR), IEEE, 2023, pp. 1134–1139.
- [20] Z. Xu, R. Hao, X. Lyu, and J. Jiang, "More sharing, more engagement? The impact of free knowledge sharing on customer engagement in online health communities," *Kybernetes*, Apr. 2024, doi: 10.1108/K-12-2023-2562.
- [21] F. Shaikh, G. Afshan, R. S. Anwar, Z. Abbas, and K. A. Chana, "Analyzing the impact of artificial intelligence on employee productivity: the mediating effect of knowledge sharing and well-being," *Asia Pacific Journal of Human Resources*, vol. 61, no. 4, pp. 794–820, 2023.
- [22] M. Hosen, S. Ogbeibu, B. Giridharan, T.-H. Cham, W. M. Lim, and J. Paul, "Individual motivation and social media influence on student knowledge sharing and learning performance: Evidence from an emerging economy," *Comput Educ*, vol. 172, p. 104262, 2021.
- [23] H. Imam and M. K. Zaheer, "Shared leadership and project success: The roles of knowledge sharing, cohesion and trust in the team," *International journal of project management*, vol. 39, no. 5, pp. 463–473, 2021.
- [24] M. Safdar, S. H. Batool, and K. Mahmood, "Relationship between self-efficacy and knowledge sharing: systematic review," *Global Knowledge, Memory and Communication*, vol. 70, no. 3, pp. 254–271, 2021.
- [25] C. Wang and Q. Hu, "Knowledge sharing in supply chain networks: Effects of collaborative innovation activities and capability on innovation performance," *Technovation*, vol. 94, p. 102010, 2020.
- [26] S. Babajani-Vafsi, J. M. Nouri, A. Ebadi, and M. Zolfaghari, "Factors influencing the participation of nurses in knowledge-sharing within mobile instant messaging based virtual communities of practice: a qualitative content analysis," *Adv Med Educ Pract*, vol. 10, pp. 897–905, 2019, doi: 10.2147/AMEP.S222779.
- [27] J. Yin, Z. Chen, M. Li, D. Zhu, and J. Guo, "Impacts of regulatory strategies on member's knowledge sharing in virtual brand communities based on ecosystemoriented business models in China," *Asia Pacific Business Review*, 2023, doi: 10.1080/13602381.2023.2281301.
- [28] S. Mustafa and W. Zhang, "Predicting users knowledge contribution behaviour in technical vs non-technical online Q&A communities: SEM-Neural Network approach," *Behaviour and Information Technology*, vol. 42, no. 15, pp. 2521–2544, 2023, doi: 10.1080/0144929X.2022.2133633.
- [29] W. Jiarui, Z. Xiaoli, and S. Jiafu, "Interpersonal Relationship, Knowledge Characteristic, and Knowledge Sharing Behavior of Online Community Members: A TAM Perspective," *Comput Intell Neurosci*, vol. 2022, 2022, doi: 10.1155/2022/4188480.
- [30] Y. Liang, T. T. Ow, and X. Wang, "How do group performances affect users' contributions in online communities? A cross-level moderation model," *Journal of Organizational Computing and Electronic Commerce*, vol. 30, no. 2, pp. 129–149, Apr. 2020, doi: 10.1080/10919392.2020.1718457.
- [31] S.-H. Tseng, T. S. Nguyen, and Y.-T. Su, "Exploring the relationship of elementary school teachers' virtual community participation on classroom management by using knowledge sharing as a mediating effect," *Interactive Learning Environments*, pp. 1– 13, Jun. 2024, doi: 10.1080/10494820.2024.2368880.



- [32] S. Sun, F. Zhang, and V. Chang, "Motivators of researchers' knowledge sharing and community promotion in online multi-background community," *International Journal of Knowledge Management*, vol. 17, no. 2, pp. 23–49, Apr. 2021, doi: 10.4018/IJKM.2021040102.
- [33] A. Razzaque, T. Eldab, and W. Chen, "Quality decisions from physicians' shared knowledge in virtual communities," *Knowledge Management Research and Practice*, pp. 1–13, 2019, doi: 10.1080/14778238.2020.1788428.
- [34] N. Wang, J. Yin, Z. Ma, and M. Liao, "The influence mechanism of rewards on knowledge sharing behaviors in virtual communities," *Journal of Knowledge Management*, vol. 26, no. 3, pp. 485–505, Mar. 2022, doi: 10.1108/JKM-07-2020-0530.
- [35] S. Mustafa, W. Zhang, and M. M. Naveed, "How to mend the dormant user in Q&A communities? A social cognitive theory-based study of consistent geeks of StackOverflow," *Behaviour and Information Technology*, vol. 43, no. 10, pp. 2024–2043, 2024, doi: 10.1080/0144929X.2023.2237604.
- [36] J. M. Matthes, X. Wang, J. Lu, and T. T. Ow, "Drivers of Knowledge Sharing in Virtual Brand Communities: Self-Determination Perspective," *Journal of Organizational Computing and Electronic Commerce*, 2024, doi: 10.1080/10919392.2024.2398913.