Research

The Effect of Self-Efficacy on Knowledge-Sharing
Behavior in Virtual Communities: The Moderating
Role of Online Informational Support

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Abstract

With the development of social media, virtual communities have become valuable platforms for knowledge sharing. However, despite the significant role virtual communities play in promoting user interaction and facilitating information exchange, the insufficient supply of knowledge has become a key factor limiting their sustained development. Therefore, identifying the factors and mechanisms that influence knowledge-sharing behavior in virtual communities is particularly important. This study aims to explore the impact of self-efficacy on knowledge-sharing behavior by constructing a comprehensive model and collecting data from 421 Chinese virtual community users through a convenience sampling online survey. The model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM), explaining the relationships between self-efficacy, attitudes toward knowledge sharing, online social support, and knowledge-sharing behavior. The results indicate that self-efficacy does not directly drive users' knowledge-sharing behavior but instead exerts an indirect influence through its effect on users' attitudes toward knowledge sharing. Additionally, the study reveals that online informational support can enhance the positive impact of self-efficacy on attitudes toward knowledge sharing. This research offers new perspectives and empirical evidence on knowledge-sharing behavior in virtual communities and provides practical guidance for community managers.

Keywords: Virtual Community, Self-Efficacy, Knowledge Sharing, Online Informational Support

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Introduction

By 2023, China's virtual community users are expected to reach 1.224 billion, with continued growth anticipated (CNNIC, 2024). Virtual communities, such as interest forums, discussion groups, and specialized social media platforms, offer immense potential by overcoming temporal and spatial limitations, facilitating knowledge sharing, and providing rich engagement experiences (Ahmed et al., 2019; Armstrong, 1996; Malinen, 2015). These communities help users forge connections and gain professional advice and support (TeBlunthuis et al., 2022). The success of virtual community hinges on active knowledge-sharing behavior, which fosters community spirit and enhances user loyalty (De Valck et al., 2009; Zhang et al., 2021). However, a major challenge is the insufficient knowledge sharing, largely due to users' reluctance to participate (Ahmed et al., 2019; Wang et al., 2021). Improving users' self-efficacy is crucial for addressing this challenge and encouraging knowledge sharing in virtual communities (Safdar et al., 2021).

In virtual communities, individuals with high self-efficacy tend to exhibit greater confidence (Ergün & Avcı, 2018). When individuals believe in their ability to share valuable knowledge, they are more likely to engage actively in knowledge sharing (Kim et al., 2020; Nguyen et al., 2019). While extensive research supports the positive influence of self-efficacy on knowledge-sharing behavior (Fang & Zhang, 2019; Lin et al., 2009), Akosile and Olatokun (2020) found that self-efficacy alone is not the sole determinant. Schunk and DiBenedetto (2021) also highlighted that, although self-efficacy is essential, motivation is affected by various factors, including personal interests and outcome expectations. Therefore, understanding knowledge-sharing behavior in virtual communities requires a comprehensive consideration of multiple factors and individual differences (Deng & Guo, 2021).

In virtual communities, online social support significantly impacts self-efficacy and knowledge-sharing behavior (Liu et al., 2019). Online social support can improve users' mental health and well-being (Zhang et al., 2022), reduce anxiety, and stimulate positive emotions and behaviors (Gilmour et al., 2020; Karagöz et al., 2021; Nick et al., 2018). Knowledge sharing in virtual communities, as a form of social interaction, fosters

information exchange, emotional expression, and mutual assistance among users with shared topics and interests (Bugshan & Attar, 2020). However, despite the recognized positive effects of social support, few studies have explored the moderating role of online informational support.

Therefore, in this study, we address the following research gaps: (1) What are the potential factors affecting users' knowledge-sharing behavior in virtual communities? (2) How do these factors influence users' knowledge-sharing behavior in virtual communities? (3) Does online informational support moderate the relationship between self-efficacy and knowledge-sharing attitudes? The ultimate goal is to provide actionable recommendations for virtual community managers.

Literature Review

Self-Efficacy and Knowledge Sharing Behavior

Bandura (1977) defines self-efficacy as an individual's belief in their ability to perform certain actions to achieve specific performance goals. Individuals tend to avoid tasks they feel are beyond their capabilities and choose tasks they believe they can handle effectively. Strong perseverance often leads to achievement, so when individuals are confident in their ability to provide valuable knowledge to others, they are more likely to overcome psychological concerns and barriers, making them more willing to share (Zhang et al., 2017). Those with high knowledge self-efficacy are likely to view knowledge sharing as a way to enhance professional authority and help others, thus being more willing to contribute actively. Conversely, individuals with low knowledge self-efficacy may feel they lack the ability to impart knowledge and may avoid sharing to protect their image and avoid revealing potential gaps in their knowledge (Lin & Huang, 2013). Therefore, we propose the following hypotheses:

H1: Self-efficacy has a positive effect on Knowledge sharing behavior in virtual communities.

Self-Efficacy and Attitude Toward Knowledge Sharing

If individuals believe that knowledge sharing is very important and feel they have sufficient ability or intrinsic motivation to address these issues, the relationship between knowledge self-efficacy and attitudes toward knowledge sharing becomes more pronounced (Chen et al., 2012; Choi et al., 2020). However, in contrast to previous studies, Chandran and Alammari (2021) found that, among various predictors of knowledge sharing in e-learning communities, the relationship between users' self-efficacy and attitudes toward knowledge sharing was not significant. This mixed research finding necessitates further investigation to confirm the relationship between self-efficacy and attitudes toward knowledge sharing. Therefore, this study proposes the following hypotheses:

H2: Self-efficacy has a positive effect on attitude toward knowledge sharing in virtual communities.

Attitude Toward Knowledge Sharing and Knowledge Sharing Behavior

Attitude refers to a psychological tendency to like or dislike something, manifested through cognitive evaluations and emotional inclinations toward that thing. It represents a mental readiness state (Ferguson & Fukukura, 2012). Behavior, on the other hand, involves a process of judgment, decision-making, and a series of observable actions. It is not only an external manifestation of underlying attitudes but is also directly influenced by those attitudes. An individual's behavioral intentions and actual behaviors are often determined by their attitudes toward specific actions (Ajzen & Fishbein, 2000). Thus, the relationship between attitudes and behaviors is very close. Additionally, attitude strength is an important factor; stronger attitudes are less likely to change and can affect information judgment and decision-making processes, thereby influencing corresponding behaviors. Fazio et al. (1986) argue that attitude strength determines whether an attitude is activated, creating internal motivation, and this strength influences whether this motivation leads to corresponding behaviors.

Therefore, we propose the following hypotheses:

H3: Attitude toward knowledge sharing has a positive effect on knowledge sharing behavior in virtual communities.

Moderating Role of Online Informational Support

Cutrona and Russell (1987) define social support as the guidance and advice provided by supporters, tangible resource assistance, positive feedback that maintains others' self-esteem, the creation of a sense of belonging, emotional comfort, and attention. Online social support, derived from the concept of social support, has rapidly developed within virtual communities. Nick et al. (2018) categorize online social support into five dimensions: emotional support, esteem support, informational support, companionship support, and tangible assistance. This study focuses on the dimension of informational support because online interactions are inherently virtual, and useful information is a primary need of community users (Yao et al., 2015). Thus, informational support better reflects the social support received by online users (Wang et al., 2021). When individuals receive positive feedback and support from other members in virtual communities, their self-efficacy is often significantly enhanced. This increased self-efficacy, in turn, motivates them to engage more confidently in knowledge-sharing activities, as they believe their knowledge and experience can add value to the community (Guan & So, 2016). Therefore, this study proposes the following hypotheses:

H4: Online informational support moderates the relationship between self-efficacy and attitudes toward knowledge sharing. Specifically, as the level of informational support increases, the positive impact of self-efficacy on attitudes toward knowledge sharing becomes stronger.

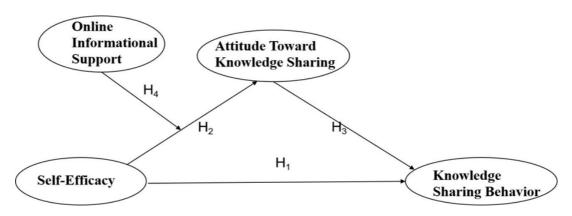


Figure 1 Conceptual Framework

Research Methodology

This study employs a quantitative research design, using constructs derived from previously established and validated scales, and incorporates all the items from these scales. For self-efficacy in knowledge sharing, we refer to the self-efficacy scale developed by Fang and Zhang (2019), which consists of 3 items. To assess attitudes toward knowledge sharing, we use scales from Bock et al. (2005), Fang and Zhang (2019), and Hau and Kim (2011), which together include 5 items. For knowledge-sharing behavior, we refer to the scale from Lin et al. (2009), which contains 5 items. Finally, for online informational support, we use the scale from Liang et al. (2011), which includes 4 items.

The questionnaire was initially in English. To reduce comprehension errors, we used the back-translation method (Brislin, 1970) to translate the scales. The questionnaire has been approved by HREC 060/2024. Given the prevalence of online surveys (Lehdonvirta et al., 2021), we distributed the questionnaire via an online platform using convenience sampling. Our target population consisted of Chinese virtual community users aged 20 to 40 who had experience with knowledge sharing in the past month, based on data indicating that this age group represents the main user base of social media platforms (KAWO, 2023). We distributed 500 questionnaires and successfully retrieved 421 valid responses, with a response rate of 84.2%. Table 1 summarizes the characteristics of the respondents.

We used two software programs to analyze the statistical data. First, we employed SPSS 27 for descriptive statistical analysis to summarize the characteristics of the respondents. Second, we used SmartPLS 4 software to conduct confirmatory factor analysis, aimed at evaluating reliability and construct validity, including convergent validity and discriminant validity. For validating the structural model, we applied the PLS-SEM method. Hair et al. (2012) highlight two significant advantages of PLS-SEM over CB-SEM: first, it relaxes the strict normality assumptions required by CB-SEM's maximum likelihood estimation; and second, it can estimate more complex models with smaller sample sizes.

Table 1 Demographics of respondents (N=421)

Male Female 205 48.7% Marital status Single 190 45.1% Married 231 54.9% Age 20-25 years old 109 25.9% 26-30 years old 109 25.9% 31-35 years old 139 33.0% 36-40 years old 64 15.2% Education High school or below 52 12.4% College 154 36.6% University 162 38.5% Graduate school or above 53 12.6% Occupation Staff in governmental units 78 18.5% Enterprise practitioners 131 31.1% Self-employed 23 5.5% Student 86 20.4% Freelancer 36 8.6% Others 67 15.9% Range of monthly	Measure	items	Frequency	Percentage (%)
Female	Gender			
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Freelancer 36 8.6% Others 67 15.9% Range of monthly disposable income Below 1000 RMB 64 15.2% 1000-3000 RMB 59 14.0% 3001-5000 RMB 122 29.0%		Self-employed	23	5.5%
Others 67 15.9% Range of monthly disposable income Below 1000 RMB 64 15.2% 1000-3000 RMB 59 14.0% 3001-5000 RMB 122 29.0%		Student	86	20.4%
Range of monthly disposable income Below 1000 RMB 64 15.2% 1000-3000 RMB 59 14.0% 3001-5000 RMB 122 29.0%		Freelancer	36	8.6%
disposable income Below 1000 RMB 64 15.2% 1000-3000 RMB 59 14.0% 3001-5000 RMB 122 29.0%		Others	67	15.9%
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3001-5000 RMB 122 29.0%		Below 1000 RMB	64	15.2%
		1000-3000 RMB	59	14.0%
5001-8000 RMB 107 25.4%		3001-5000 RMB	122	29.0%
		5001-8000 RMB	107	25.4%

Measure	items	Frequency	Percentage (%)
	More than 8000 RMB	69	16.4%
Total		421	100%

Results

Measurement Model Analysis

When analyzing the measurement model using the PLS algorithm in SmartPLS 4.0, the computation settings were as follows: the weighting scheme was set to "Path," and the result type was set to "Standardized." The quality of constructs in the study was determined based on the evaluation of the measurement model. The quality assessment began with the evaluation of outer loadings, followed by the establishment of construct reliability and validity (Table 2).

All item factor loadings in this study were above the recommended threshold of 0.50 (Hair et al., 2011). Therefore, no items were removed further. Cronbach's Alpha values ranged from 0.841 to 0.910, while the composite reliability statistics ranged from 0.904 to 0.933. Both reliability indicators exceeded the required threshold of 0.70 (Cronbach, 1951), establishing construct reliability. Convergent validity was established when the AVE values were greater than or equal to the recommended value of 0.50 (Fornell & Larcker, 1981). The results of convergent validity based on AVE statistics in the current study show that all constructs had AVE values greater than 0.50, indicating good convergent validity.

Table 2: Reliability and validity analysis

Construct	Item	Loading	Alpha	CR	AVE
	SE1	0.894			
Self-efficacy(SE)	SE2	SE2 0.833 0.841	0.841	0.904	0.758
	SE3	0.885			
Attitude toward to end edge sharing (AT)	AT1	0.863	0.878	0.011	0.672
Attitude toward knowledge sharing (AT)	AT2	0.828	0.078	0.911	0.673

Construct	Item	Loading	Alpha	CR	AVE
	AT3	0.780			
	AT4	0.800			
	AT5	0.829			
	BE1	0.877			
Ka ayda daa ahayina	BE2	0.875			
Knowledge sharing	BE3	0.843	0.910	0.933	0.735
behavior (KSB)	BE4	0.827			
	BE5	0.864			
	IS1	0.854			
Online informational	IS2	0.886	0.077	0.045	0.700
support	IS3	0.842	0.877	0.915	0.728
(IS)	IS4	0.831			

According to Fornell and Larcker (1981), discriminant validity is established when the square root of a construct's AVE (Average Variance Extracted) is greater than its correlations with all other constructs. In this study, the square root of each construct's AVE (bold and italicized) was found to be greater than its correlations with other constructs. This provides strong support for the establishment of discriminant validity.

Table 3: Discriminant Validity

	SE	AT	KSB	IS
SE	0.871			
AT	0.491	0.820		
KSB	0.230	0.424	0.858	
IS	0.056	0.156	0.006	0.854

Notes: Diagonal and italicized are the square roots of the AVE. Below the diagonal elements are the correlations between the construct's values.

Abbreviations: SE, Self-efficacy; AT, Attitude toward knowledge sharing; KSB, Knowledge sharing behavior; IS, Online informational support

Structural Model Assessment

The structural model was evaluated to assess the structural paths, analyze path coefficients (relationships between constructs), and determine their statistical significance. The data, sourced from the survey, may be subject to common method bias. To test this, the Harman single-factor method was used. The results showed that the variance explained by the unrotated first factor was 33.40%, which is below the 50% threshold (Aguirre-Urreta & Hu, 2019). Therefore, common method bias is not present. We then assessed the model fit, with the results presented in Table 4.

Table 4: Model fit

	Saturated model	Estimated model
SRMR	0.042	0.044
d_ULS	0.264	0.303
d_G	0.13	0.132
Chi-square	369.868	375.433
NFI	0.918	0.917

Path analysis was conducted using the bootstrap algorithm with the following computation settings: the weighting scheme was set to "Path," 5000 bootstrap samples were used, the confidence interval method was chosen as Bias-corrected and accelerated (BCa) bootstrap, the test type was two-tailed, and the significance level was set at 0.05. The test results are summarized in Table 5. The R² value for the endogenous structure of KSB is 0.181, which indicates an explanatory strength of moderate (Cohen, 1988).

Table 5: Hypothesis Testing

	Path	SD	Т	Р	Hypothesis test
	coefficient		values	values	results
H1:SE -> KSB	0.028	0.040	0.685	0.493	Not supported
H2:SE -> AT	0.486***	0.040	12.062	0.000	Supported
H3:AT -> KSB	0.411***	0.050	8.227	0.000	Supported
H4:IS × SE -> AT	0.163***	0.044	3.743	0.000	Supported

Abbreviations: SE, Self-efficacy; AT, Attitude toward knowledge sharing; KSB, Knowledge sharing behavior; IS, Online informational support.

The path coefficients and significance values for the main effects are shown in Figure 2. H1 tested if self-efficacy affects knowledge-sharing behavior. The results showed no direct effect (β = .028, t = 0.685, p = 0.493), so H1 is not supported. H2 examined if self-efficacy influences attitudes toward knowledge sharing. The results indicated a significant impact (β = .163, t = 12.062, p < 0.001), thus H2 is supported. H3 investigated whether attitudes toward knowledge sharing affect knowledge-sharing behavior. The findings showed a significant effect (β = .411, t = 8.227, p < 0.001), so H3 is supported. H4 assessed if online informational support moderates the relationship between self-efficacy and attitudes toward knowledge sharing. The results confirmed that it does (β = .163, t = 3.743, p < 0.001), so H4 is supported.

We analyzed the mediating role of attitudes toward knowledge sharing (see Table 6) and found they significantly mediate the relationship between self-efficacy and knowledge sharing behavior (β = .200, t = 6.763, p < 0.001). Based on Hair et al. (2014), a VAF value over 80% indicates full mediation. With a VAF of 88.11% (0.200/0.227 = 0.881), attitudes toward knowledge sharing fully mediate the effect of self-efficacy on knowledge sharing behavior.

Table 6: Mediation analysis

Path	Path	Indirect Effect	SD	T Value	97.5% LLCI	97.5% ULCI	VAF
AT -> KSB	0.411		0.050	8.227	0.308	0.504	
SE -> AT	0.486		0.040	12.062	0.403	0.562	
SE -> KSB	0.227		0.046	4.992	0.138	0.316	
SE -> AT		0.200	0.030	6.763	0.143	0.260	88.11%
-> KSB		0.200	0.030	0.105	0.143	0.200	00.1170

Abbreviations: SE, Self-efficacy; AT, Attitude toward knowledge sharing; KSB, Knowledge sharing behavior; IS, Online informational support. LLC: lower limit confidence interval, ULCI: upper limit confidence interval.

We analyzed the moderating effect of online informational support (see Table 7). The results indicate that the interaction effect of self-efficacy and online informational support on attitudes toward knowledge sharing is significant (β = .163, t = 3.743, p < 0.001), suggesting a positive impact. Higher perceived online informational support enhances the positive effect of self-efficacy on attitudes toward knowledge sharing. Additionally, the interaction between self-efficacy and online informational support also affects knowledge-sharing behavior (β = .067, t = 3.358, p < 0.01).

Table 7: Moderating analysis

	Path coefficient	SD	T values	P values
IS x SE -> AT	0.163	0.044	3.743	0.000
IS x SE -> KSB	0.067	0.020	3.358	0.001

Abbreviations: SE, Self-efficacy; AT, Attitude toward knowledge sharing; KSB, Knowledge sharing behavior; IS, Online informational support.

Conclusion and Discussion

The main objective of this study is to explore how self-efficacy influences knowledge-sharing behavior in virtual communities. The findings reveal that self-efficacy does not directly predict knowledge-sharing behavior, as noted by Akosile and Olatokun (2020), who observed that confidence in one's ability to provide knowledge does not always translate into actual sharing behavior. This result aligns with Choi et al. (2020) and Chen et al. (2012), who found that confidence in one's ability to contribute valuable knowledge fosters more positive attitudes and greater motivation to share knowledge with others. Additionally, the study validates the important role of attitudes toward knowledge sharing. In virtual communities, self-efficacy fully mediates the relationship between attitudes and actual knowledge-sharing behavior. This suggests that when community

members believe that sharing knowledge benefits others, they are more inclined to engage in knowledge sharing. This finding is consistent with Bock et al. (2005) and Fang and Zhang (2019).

Moreover, the study confirms the moderating effect of online informational support, affirming the role of social support in virtual communities. As Prescott et al. (2019) noted, supportive online environments facilitate problem-solving, knowledge sharing, and emotional exchange, thereby enhancing user connections, emotional well-being, and confidence. This aligns with research by Karagöz et al. (2021) and Zhang et al. (2022), highlighting the importance of social interaction and a sense of belonging in online settings. Online informational support reduces anxiety and strengthens the link between behavior intention and positive emotions, leading to increased positive behavior and self-confidence.

Theoretical Implications

This study offers a new perspective on understanding the relationship between self-efficacy and knowledge-sharing behavior. While previous research has highlighted the impact of self-efficacy on knowledge sharing (Safdar et al., 2021), this study further reveals the mediating role of attitudes toward knowledge sharing. Self-efficacy, as a powerful predictor, does not always directly influence behavior; instead, it first affects individual attitudes, which in turn impact behavior. This indirect mechanism provides a new theoretical framework for understanding the relationship between self-efficacy and knowledge-sharing behavior.

The findings of this study are significant for enhancing our understanding of social support and knowledge-sharing behavior in virtual communities. By examining the moderated mediation model, we reveal how user attitudes toward knowledge sharing mediate the relationship between self-efficacy and knowledge-sharing behavior, and how this mediation effect is strengthened by the level of online informational support. This insight is valuable for both theoretical development and practical application.

Previous research has typically explored online informational support as an independent variable (Chiu et al., 2015; Zhu et al., 2016; Wang et al., 2021) or a mediator

(Kim & Lee, 2011; Chun & Lee, 2017) in virtual environments, with less emphasis on its role as a moderator. However, interaction in virtual communities profoundly impacts individuals' psychological perceptions. Positive online informational support often leads to favorable psychological experiences and enhanced motivation to engage. It not only provides necessary information and resources but also satisfies individuals' social needs in virtual environments (Zhang & Liu, 2022). Through affirmation and recognition from others, individuals experience a sense of belonging and value, which further enhances their self-efficacy and drives them to share knowledge more actively.

Managerial Implications

Understanding knowledge-sharing behavior in virtual communities helps platform designers and managers understand user needs and preferences. To boost knowledge sharing, it's crucial to simplify content posting and create a supportive community atmosphere. Firstly, an intuitive interface that simplifies posting text, images, and videos enhances user experience and increases engagement by boosting self-efficacy and participation. Secondly, fostering a positive community environment with rewards like points and badges, and hosting online events, encourages user interaction and enthusiasm, leading to more active knowledge sharing. Finally, leveraging user-shared knowledge, such as feedback on products and services, can benefit commercial stakeholders. Brands can gain market insights and refine offerings, while advertisers can target ads more effectively. This approach not only enhances commercial prospects and brand visibility but also supports community growth, attracting more users.

Limitations

This study has several limitations. First, the survey was conducted exclusively in China, which may limit the generalizability of the findings to other cultural and social contexts. Second, as a self-report method, the survey may be subject to biases related to social desirability or self-perception, affecting the accuracy of the responses. Lastly, the research employs a cross-sectional design, capturing data at a single point in time, which restricts the ability to track and analyze long-term knowledge-sharing behaviors.

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