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The Combinatory Effects of Social Media Affordances on Knowledge Contribution Quality in Virtual Communities

Ying Yue[1,2], Cheng-Hu Zhang[1*], Le Geng[3], and Dong-Han Wang[1]

[1] School of Economics and Management, Communication University of China,
Beijing 100024, China

yueyingts@126.com, zhangchenghu@cuc.edu.cn, gengle@hbjd.edu.cn,
2023100503z3079@cuc.edu.cn

[2] Tangshan Vocational & Technical College,
Tangshan City 063017, Hebei province, China

[3] Hebei Institute of Mechanical and Electrical Technology,
Xingtai City 054000, Hebei Province, China

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Abstract. This study constructs a configurational framework to examine how synergistic interactions among four social media affordances—metavoicing, triggered attending, network-informed associating (follower/followed), and generative role-taking (public editor/platform arbitration)—drive high-quality knowledge contributions in virtual communities. By prioritizing combinatorial causality over isolated factors, it addresses gaps in understanding how platform design sustains user engagement through socio-technical affordance interactions. Using fuzzy-set Qualitative Comparative Analysis (fsQCA), we analyzed behavioral data from 322 active contributors and 14,669 contributions on Zhihu (June-July 2024). Six affordance dimensions were calibrated to identify configurational pathways, emphasizing non-linear interactions and equifinality in achieving high-quality outcomes. Ten configurations, categorized into four pathways (network-, metavoicing-, role-, and triggered-association-driven), revealed that network-informed associating (follower/followed) and metavoicing are core drivers. Triggered attending and generative role-taking enhance contributions only in specific contexts. No single factor is necessary; outcomes depend on combinatorial synergies. This study pioneers a configurational lens to decode interdependencies among social media affordances, empirically validating their combinatorial effects on knowledge quality. It advances socio-technical theory by bridging affordance design and user behavior, offering actionable strategies to optimize virtual communities—aligning with human-technology interaction and practical innovation.

Keywords: affordance, virtual communities, knowledge contribution behavior, configurational perspective

1 Introduction

Virtual communities are cyberspace for knowledge exchange [1] that play a crucial role in information sharing and production [2]. The knowledge contributed by members is a key factor for a platform's sustainable development and commercial value, making it a major challenge to stimulate active user participation.

However, many communities suffer from significant participation inequality, where a small fraction of users generates the majority of the content [3]. Most current research focuses on the motives and influencing mechanisms of user participation in knowledge contribution, primarily examining the effects of individual motivations [4], platform factors [5-6] and social networks [7] on knowledge contribution behaviors. However, there has been limited attention to the quality of knowledge-contributing behavior [8].

Previous research has often prioritized the quantity of contributions over their quality. Yet, as Wasko and Faraj [9] noted, quality is often more critical for a community's long-term success. Understanding the mechanisms that drive high-quality contributions is therefore essential for the sustainable development of virtual community platforms.

This paper addresses this gap by exploring how social media affordances impact the quality of knowledge contributions. Using fuzzy-set Qualitative Comparative Analysis (fsQCA), this study investigates the configu-

* Corresponding Author

rational paths that lead to high-quality outcomes. Specifically, we ask: (1) What are the key social media affordances in virtual communities? (2) How do combinations of these affordances influence the quality of knowledge contribution? This research aims to provide theoretical and practical insights for improving knowledge contribution quality in virtual communities.

2 Background Literature and Theoretical Underpinnings

2.1 Knowledge Contribution Behavior in Virtual Community

A virtual community is an online network where users interact to build social relationships and share knowledge, often centered on shared interests, hobbies, goals, and language [10]. These communities can be primarily content-oriented, like Wikipedia [11], or relationship-oriented, like Facebook [12]. In knowledge-focused virtual communities, such as Q&A platforms like Zhihu, these characteristics are reinforced by the additional element of knowledge sharing [13], which serves as both the primary mode of interaction and the central mechanism for community cohesion [14].

Within these communities, knowledge sharing is the process of disseminating expertise. Knowledge contribution is an extension of this, involving the active creation of value for the community by answering questions and publishing content that others can build upon, which is vital for sustained growth. This behavior involves externalizing explicit and tacit knowledge through actions like sharing experiences or creating content, which are central to the community's resilience. While broadly defined as any valuable activity, it is often restricted to core acts like answering questions and writing articles.

Existing literature has focused on the factors and mechanisms influencing knowledge contribution [15]. While research agrees that social connection positively impacts contribution, findings on its effect on quality are inconsistent; some studies find a positive link [16] while others do not [17]. Key gaps remain in the research: most studies focus on contribution quantity over quality, examine quality from the receiver's perspective rather than the platform's role, and use single-item measures for contribution quality, limiting the depth of insight.

Research has identified multifaceted factors influencing knowledge contribution, drawing from various psychological and sociological theories. Studies consistently highlight the role of intrinsic motivations, such as altruism and self-efficacy, alongside extrinsic motivators like peer recognition and rewards. Social dynamics are also critical [18]; social capital theory emphasizes how trust and network structures foster engagement [19] while social exchange theory points to expectations of reciprocity [20]. Other perspectives confirm that user identity significantly impacts sharing behaviors [21].

However, current research exhibits notable gaps. The focus has predominantly been on these individual-level factors, often neglecting the direct influence of the virtual community platform itself—its features, feedback mechanisms, and culture. Furthermore, while the importance of knowledge quality is acknowledged, few studies investigate the specific platform-level mechanisms that drive high-quality, sustainable contributions [22]. Given the increasing importance of social media affordances in shaping user engagement, investigating how these affordances impact high-quality knowledge contribution is crucial for understanding the underlying mechanisms that drive sustainable participation.

2.2 Virtual Community and its Affordances

The concept of affordances, originating from Gibson [23], posits that individuals perceive objects through the potential actions they enable. This relational perspective emphasizes the interplay between an observer and their environment, suggesting that technology use requires consideration of both its material properties and human agency [24]. In digital media, affordances are the action potentials offered to users [25], which are distinct from the outcomes users achieve through engagement [26].

In virtual communities, social media affordances facilitate the user interaction, content sharing, and communication essential for high-quality knowledge contribution. Majchrzak et al. [27] identify four key affordances: metavoicing, triggered attending, network-informed associating, and generative role-taking. However, the discourse is not without contention; some scholars argue that certain features may not qualify as true affordances, prompting further investigation into how they manifest in user behavior [28].

Despite existing literature, a notable gap remains in understanding the affordances of virtual communities, particularly their impact on high-quality knowledge contribution. The dynamic interplay between social media affordances and the quality of contributions is underexamined, highlighting a need for empirical testing to address theoretical debates.

2.3 Summary

Existing research highlights the role of social factors, user motivations, and technological affordances in shaping knowledge contribution. However, significant gaps persist: prior studies often focus on contribution quantity over quality and overlook how platform affordances specifically influence high-quality outcomes. Furthermore, theoretical disputes remain regarding the definition and impact of affordances.

This paper aims to address these gaps by examining how social media affordances influence high-quality knowledge contribution behavior in virtual communities. By exploring this relationship, the study seeks to provide a nuanced understanding of the mechanisms that support high-quality engagement and knowledge sharing in digital spaces. This research is necessary for offering insights into fostering sustainable, valuable user contributions, which are essential for the competitive advantage and growth of virtual communities. The research framework is shown in Fig 1.

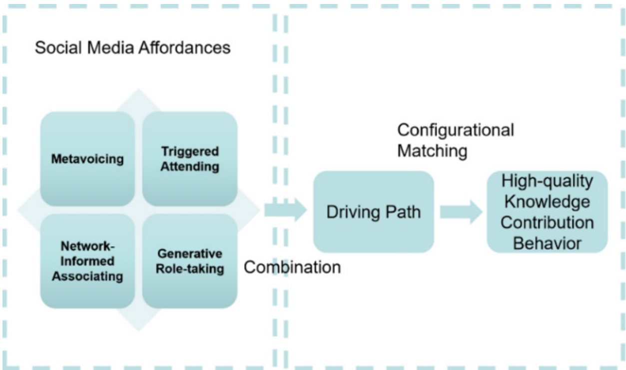

Fig. 1. Research framework

3 Research Data and Methodology

3.1 Data Source

The empirical focus of this paper is the quality of knowledge contribution in virtual communities. Knowledge-based Q&A communities are ideal settings for this research, as their primary purpose is knowledge exchange. For this study, we selected the Zhihu platform as our data source. Zhihu is a prominent social Q&A community with a large, diverse user base and an open data structure that supports empirical research. Its features, which facilitate both social interaction and in-depth knowledge sharing, make it a representative case for analyzing the impact of social media affordances on contribution quality. For this study, knowledge contributions are defined as user activities (publishing ideas, answering questions, or posting articles) that receive at least one "like."

A total of 479 new knowledge contributors, selected annually by the Zhihu platform from the decade preceding 2020 and from each year between 2020 and 2023, served as the sample of knowledge contributors. Their contributions spanned 53 fields, including humanities, film and television, health, science, and fashion. The Zhihu platform designates a group of respondents from various domains each year, awarding them the title of "New Knowledge contributors". These individuals represent typical contributors on the platform, reflecting diverse knowledge-sharing patterns and aiding the analysis of both the quality of knowledge contributions and the underlying affordance factors. Furthermore, the core functions and incentive mechanisms of the Zhihu platform have remained relatively stable over the years, allowing this cross-temporal sample to demonstrate the sustained impact of platform features on user behavior without the complications of changing functionalities. The basic information of 479 new knowledge contributors and their dynamic behavior data from June to July 2024 were crawled, as shown in Table 1.

Table 1. Information table of knowledge contribution data of new knowledge contributors

Annual	Number of users	Number of duplicate users	The number of users with dynamics	The number of users who contributed knowledge	Number of ideas posted, questions answered, articles published	Number of knowledge contributions
2010-2019	83	0	55	47	2755	2752
2020	101	10	70	57	3653	3639
2021	97	15	50	43	782	755
2022	99	1	93	90	3584	3509
2023	99	11	86	85	4162	4162
Total	479		354	322	14936	14669

After data cleaning, which involved removing duplicate respondents, deactivated accounts, and users without activity during the observation period, a sample of 354 new knowledge respondents who had actively shared knowledge was obtained. The sample users contributed knowledge on the Zhihu platform through various formats, including posting ideas, answering questions, and publishing articles, resulting in a total of 14,936 contributions. During the data collection period, 322 users received at least one upvote for their contributions, indicating that their activities reflected meaningful knowledge contributions, totaling 14,669 contributions.

3.2 Variable Definition and Measurement

Outcome Variable: Quality of Knowledge Contribution. The previous research has typically employed several main measurement methods. First, the quantity measurement method focuses on the number of answers users post. However, this approach overlooks the quality of answers and the feedback from user interactions. Second, the quality measurement approach emphasizes that both the quantity and quality of knowledge are important. Lastly, some studies adopt a multidimensional evaluation method that combines various indicators to provide a more comprehensive reflection of the contributions' impact.

We define knowledge contribution quality (KCQ) as "the average number of likes received by a knowledge contributor." This is calculated by dividing the sum of likes received for a contributor's ideas, answers, and articles by their total number of contributions. This metric integrates both quantity and quality, allowing for a more accurate assessment of a contribution's recognized value. By emphasizing community recognition, this method effectively identifies high-quality knowledge and avoids the biases of purely quantitative measures, providing a solid foundation for analyzing knowledge sharing in a social media environment. The definition of high-quality knowledge as an answer that receives at least one upvote within a month of posting. Additionally, calculating the ratio of likes to contribution quantity enhances the sensitivity of the assessment, avoiding biases associated with purely quantitative measures. This operationalization specifically isolates the intensity of quality from the mere volume of activity, mitigating the bias where high-frequency contributors might accumulate total likes purely through prolixity rather than depth of insight. This aligns with the platform›s mechanism where high-quality content is algorithmically surfaced based on engagement rates per impression.

Antecedent Variables. In this study, the selection of antecedent variables—Metavoicing, Triggered Attending, Network-informed Associating, and Generative Role-taking—was guided by their relevance to the research problem and the ongoing theoretical controversies surrounding social media affordances.

Metavoicing (MV) refers to users' feedback on others' content through likes, comments, shares, and other interactive behaviors. This engagement fosters knowledge interaction within the platform and incentivizes contributors to continue sharing their insights. We measure this affordance by the number of upvotes received for answers, articles, and ideas shared by contributors on the Zhihu platform. Research indicates that positive feedback, such as likes, significantly enhances users' willingness to contribute and improves the quality of their subsequent submissions。Furthermore, an increase in upvotes bolsters contributors' reputations and facilitates the dissemination of high-quality knowledge within the community. Therefore, Metavoicing plays a crucial role in influencing both the quantity and quality of knowledge contributions through a positive feedback mechanism.

Triggered attending（TA）refers to how community users engage in online knowledge conversations by remaining passive until timely automated notifications alert them to updates on specific content of interest. Users can follow particular topics, columns, or issues, which encourages them to maintain their focus on areas that interest them, thereby prompting deeper discussions and knowledge contributions within those domains. This availability is measured by the number of Followed Topics, Followed Columns, Followed Sections, and Followed Questions. By following content in relevant fields, users gain access to professional knowledge and discussions in a more timely manner, which enhances their contributions in these areas.

Network-informed associating (NA) involves engaging in online knowledge conversations that are shaped by relationships and content connections. This interconnectedness influences users' knowledge contributions through their established social networks. We measure this affordance using two indicators: the number of knowledge contributors who follow others (Followed) and those who are followed by others (Followers) on the Zhihu platform. Extensive social networks can enhance users' access to diverse sources of information, thereby improving the quality of their knowledge contributions. Contributors who are followed by a larger number of users enjoy increased opportunities for discussion and feedback, which further incentivizes them to produce more high-quality knowledge.

Generative role-taking (GRT) involves engaging in online knowledge sharing through patterned actions that sustain a community, thereby fostering productive dialogue among participants. Social media facilitates this process by increasing the visibility of conversations, which accentuates the need for dialogue. We measure this affordance using two indicators: the number of public edits made by knowledge contributors on the Zhihu platform and their status as Zhihu arbitrators. Users who are actively involved in content editing often enhance the accuracy and authority of the platform's information, which, in turn, improves the overall quality of knowledge in the community. Furthermore, when users assume the roles of content producers and maintainers, they become more conscious of the quality of their contributions, understanding their reputation and responsibility within the community.

Additionally, the public judge system on the Zhihu platform serves as a mediation mechanism. We assess this affordance by determining whether a user holds the status of a public judge. Mediators not only help maintain a healthy community atmosphere but also accumulate the ability to evaluate content quality through dispute resolution and information accuracy assessment. These mediators often possess higher levels of knowledge and community reputation, enabling them to lead in knowledge contributions and promote more high-quality knowledge sharing.

The data collection and measurement results of the variables are shown in Table 2.

Table 2. Variables definition and description

Type of variable	Affordance dimension	Variable	Symbol	Measure item
Dependent variable	Knowledge contribution quality	Average number of likes	KCQ	The quotient of the sum of the number of approvals received by a knowledge contributor who posts an idea, answers a question, or publishes an article divided by the number of knowledge contributions
Independent variables	Metavoicing	Upvotes	MV	The number of answers, articles, ideas that knowledge contributor endorsed other users
	Triggered attending	Focus on the topic	TA	The number of topics, columns, questions, and favorites followed by the knowledge contributor
	Network-informed associating	Followed	FOD	The number of other users followed by the knowledge contributor
		Follower	FOR	The number of users who follow the knowledge contributor
	Generative role-taking	Public editor	PE	The number of times a knowledge contributor participate in public editing.
		Platform arbitration	PA	Whether to serve as Zhihu referee officer

Knowledge contribution quality is represented as the result variable, calculated by dividing the total number of upvotes received by knowledge contributors for their ideas, answers, and articles by the total number of knowledge contributions made. The predictor variables include Metavoicing (MV), Triggered Attending (TA), Network-informed Associating (Followed, FOD and Followers, FOR), Generative Role-taking (GRT), and Mediatory Engagement (ME). All variables are statistically analyzed using count data from the Zhihu platform, with descriptive statistics including maximum values, minimum values, and variance (see Table 3).

Table 3. Population characteristics of the sample

Affordance dimensions	Variable	Symbol	Cases	Mean	Std. Dev.	Minimum	Maximum
Knowledge contribution quality	Average number of likes	KCQ	322	178.5828	451.3717	1	4713
Metavoicing	upvotes	MV	322	77.67702	210.504	0	2467
Triggered attending	Focus on the topic	TA	322	1621.199	2377.77	5	24511
Network-informed associating	followed	FOD	322	525.2174	967.9027	0	13000
	follower	FOR	322	36.73662	45.9407	0	346
Generative role-taking	Public editor	PE	322	991.0776	7273.78	0	111452
	Platform arbitration	PA	322	0.4906832	0.4999132	0	1

3.3 Research Methodology

This study aims to identify the configurational paths through which virtual community affordances impact high-quality knowledge contributions. Because knowledge contribution is a complex process driven by the interplay of multiple factors, traditional linear statistical methods are often inadequate. We therefore employ fuzzy-set Qualitative Comparative Analysis (fsQCA), a method that integrates qualitative and quantitative strengths to analyze how combinations of conditions produce an outcome. fsQCA is particularly suited for this research as it: (1) identifies the joint effects of multiple affordances rather than the net effect of individual factors; (2) addresses the "equifinality" inherent in complex social phenomena, where multiple causal paths can lead to the same outcome; and (3) captures the nuanced effects of varying degrees of the antecedent conditions.

The analysis is based on the set-theoretic principles of sufficiency and necessity, which are evaluated using consistency and coverage metrics. A configuration is considered sufficient for the outcome (KCQ) if cases with high membership in the configuration consistently exhibit high membership in the outcome ($X \subseteq KCQ$). The parameters are calculated as follows:

Following set-theoretic principles, we assess the sufficiency of affordance configurations using consistency and coverage metrics. Consistency measures the degree to which cases sharing a specific configuration of affordances (denoted as set X) also exhibit high knowledge contribution quality (set KCQ). It is calculated as the intersection of the configuration and the outcome divided by the sum of the configuration memberships (Eq. 1).

Let X represent a specific antecedent configuration and Y represent the outcome variable KCQ. μx_i denotes the membership degree of case i in configuration X (determined by taking the minimum value of the intersection). Assesses the empirical relevance of a sufficient configuration, analogous to the effect size. It is calculated as the proportion of the outcome set covered by the configuration:

$$\mu x_i = min(\mu MV_i, \mu TA_i, \mu FOD_i, \mu FOR_i, \mu PE_i, \mu PA_i) \quad \textbf{(1)}$$

This expression formalizes the fuzzy-set intersection used to derive configurational membership for case *i*.

To complement the traditional minimum operator used in fsQCA, we introduce an alternative fuzzy intersection operator from fuzzy logic — the Lukasiewicz t-norm. Unlike the minimum (strict conjunctive) and multiplicative (geometric) operators, the Łukasiewicz t-norm permits limited compensatory trade-offs among causal conditions while preserving fuzzy-set boundary constraints. This operator is particularly useful when multiple moderately strong conditions together should produce high configurational membership even if no single condition is maximal.

$$\mu X_i = max\left(0, \sum_{k=1}^{6} \mu_{k,i} - (6-1)\right) \quad \textbf{(2)}$$

$u_{k,i}$ represents the fuzzy-set membership of case *iii* in the *kkk−th* antecedent condition.

$$\text{Consistency}(X \subseteq KCQ) = \frac{\sum_{i=1}^{n} \min(\mu x_i, \mu KCQ_i)}{\sum_{i=1}^{n} \mu x_i} \quad (3)$$

$$\text{Coverage}(X \subseteq KCQ) = \frac{\sum_{i=1}^{n} \min(\mu x_i, \mu KCQ_i)}{\sum_{i=1}^{n} \mu KCQ_i} \quad (4)$$

Here, consistency measures the degree to which a causal configuration leads to the outcome, while coverage assesses the empirical relevance or importance of that configuration in explaining the outcome.

Conversely, a single condition (X) is considered necessary for the outcome if the outcome is a subset of the condition ($KCQ \subseteq X$), meaning the outcome is not present without the condition. The parameters for necessity are:

$$\text{Consistency}(X \supseteq KCQ) = \frac{\sum \min(\mu x_i, \mu KCQ_i)}{\sum KCQ_i} \quad (5)$$

$$\text{Coverage}(X \supseteq KCQ) = \frac{\sum \min(\mu x_i, \mu KCQ_i)}{\sum x_i} \quad (6)$$

In fuzzy-set logic, a condition is considered necessary for an outcome when the outcome set is fully included in the condition set. This inclusion relationship is expressed mathematically as follows:

$$Y \subseteq X \Leftrightarrow \forall i, \mu Yi \le \mu Xi \quad (7)$$

This study constructs a configurational model to explore how six antecedent conditions—Metavoicing (MV), Triggered Attending (TA), Network-informed Associating (Followed, FOD; and Followers, FOR), and Generative Role-taking (Public Editor, PE; and Platform Arbitration, PA)—combine to influence the outcome, high-quality knowledge contribution (KCQ). The general form of this model, expressed using Boolean algebra, is:

$$\text{Minimize: } F = \sum (C_i) \rightarrow KCQ \quad (8)$$

The final configurations are derived using Boolean minimization based on the Quine-McCluskey algorithm. The core logic follows the principle that if an outcome KCQ occurs regardless of the presence or absence of a specific condition, that condition is considered logically redundant and can be eliminated from the specific path. Mathematically, this reduction is expressed as A·B+A·~B→A, where A represents the core configuration and *B* represents the redundant condition.

The minimization process relies on Boolean algebra, particularly the absorption law, which allows logically redundant conditions to be removed from a configuration:

$$AB + \overline{AB} = A \quad (9)$$

This principle underlies the Quine–McCluskey minimization procedure used in fsQCA.

By collecting the basic information and dynamic behavior data of knowledge contributors and analyzing the data from knowledge contribution behavior samples, the fsQCA method clarifies the complex causal relationships between the affordances of social media in virtual communities and high-quality knowledge contribution behaviors. Through necessity analysis, the study tests whether there exists a single affordance factor driving the high-quality knowledge contributions of knowledge contributors. Additionally, through conditional configuration adequacy analysis, it identifies the complex driving paths for high-quality knowledge contributions, exploring which combinations of affordances can more effectively drive such contributions.

3.4 Fuzzy-set Variable Calibration

Data calibration is a crucial step when performing a fuzzy set qualitative comparative analysis (fsQCA), which requires the researcher to convert the raw data into membership scores in the fuzzy set to reflect the membership degree of each case under different conditions. Based on the study of Fiss [29] and Codurasa [30], the software assignment method of data distribution was used for calibration.

This method combines the data types of each condition and outcome variable, and uses the software to automatically determine the membership threshold, so as to improve the objectivity and accuracy of the calibration process, and determine the specific percentile of the data distribution as the threshold of full membership, intersection point, and complete non-membership, which can reasonably distinguish the status of cases under different conditions. By observing the sample data and combining it with the actual situation, setting the 90%, 50%, and 10% quantiles can be used to adjust the influence on the extreme values to better capture the intermediate trend of the data, so as to avoid the excessive influence of the extreme values on the results [31].

Table 4. Antecedent and result conditions calibration points for the sample data (0.9 0.5 0.1)

Affordance dimensions	Variable	Symbol	Affiliation	Intersections	Not affiliated
Knowledge contribution quality	Average number of likes	KCQ	321.91	65.12	11.93
Metavoicing	Upvotes	MV	186.80	12.50	0.00
Triggered attending	Focus on the topic	TA	3346.80	935.50	189.90
Network-informed associating	Followed	FOD	1107.30	300.50	45.00
	Follower	FOR	89.01	19.90	5.25
Generative role-taking	Public editor	PE	1041.70	136.00	9.00
	Platform arbitration	PA	-	-	-

This method of determining the value takes into account the longitudinal development of the data, which makes the calibrated benchmark data more convincing. Because the Generative role taking-Platform Arbitration (PA) itself is a Boolean value, there is one result and five condition variables that need to be calibrated, and the threshold results after fuzzy set calibration are shown in Table 4.Then, the calibrate function in the fsQCA software is used to convert the original data into fuzzy set data between 0 and 1 according to the threshold. The converted Knowledge Contribution Quality (KCQ), Metavoicing (MV), Triggered Attending (TA), Network-informed Associating-Followed (FOD), Network-informed Associating-Follower (FOR), and Generative Role-taking-Public Editor (PE) are denoted as FKCQ, FMV, FTA, FFOD, FFOR, and FPE, respectively.

The complete calibration procedure can be conceptualized as a two-stage transformation from raw data to fuzzy-set membership scores:

$$x_i \rightarrow \mathrm{log}it(x_i) \rightarrow \mu_i \tag{10}$$

To rigorously verify the calibration process, we employ the **Direct Method** of calibration outlined by Ragin (2008), which transforms raw interval-scale data into fuzzy membership scores (μ_x) using a logistic transfer function. This process relies on the specification of three qualitative anchors: the threshold for full inclusion (T_{inc}, membership ≈ 0.95, the crossover point of maximum ambiguity (T_{cross}, membership=0.5), and the threshold for full exclusion (T_{exc}, membership ≈ 0.05).

The transformation proceeds in two distinct steps: (1) calculating the log-odds of membership based on the deviation of raw scores from the crossover anchor, and (2) converting these log-odds into membership scores bounded between 0 and 1.

Step 1: Piecewise Derivation of Log-Odds

Given the inherent asymmetry in social media behavioral data (e.g., the "superstar effect" on Zhihu where top-tier metrics exponentially exceed the median), a simple linear transformation is insufficient. We calculate the log-odds ($logit_i$) for each case i using separate scalars for values above and below the crossover point to preserve the distributional integrity of the data.

We define the log-odds of full inclusion as ln(0.95/0.05) ≈ 3 and full exclusion as ln(0.05/0.95) ≈ -3. The calibrated log-odds are derived as follows:

$$logit_i = \begin{cases} \dfrac{3\cdot(x_i - T_{cross})}{T_{inc} - T_{cross}}, if\ x_i > T_{cross} \\ \dfrac{3\cdot(x_i - T_{cross})}{T_{cross} - T_{inc}}, if\ x_i \le T_{cross} \end{cases} \quad (11)$$

Where x_i is the raw value for case i. This piecewise formulation ensures that the slope of the calibration function adapts to the specific dispersion of data on either side of the qualitative anchor, accurately reflecting the intensity of affordance actualization.

Step 2: The Logistic Transfer Function Once the generalized log-odds are computed, the fuzzy membership score μx_i is obtained using the inverse logit function. This corrects the notation from the original manuscript:

$$\mu_{x,i} = \frac{\exp(\mathrm{logit}_i)}{1+\exp(\mathrm{logit}_i)} = \frac{1}{1+e^{-\mathrm{logit}_i}} \quad (12)$$

Beyond the logit-based calibration, the general form of fuzzy membership can also be expressed using a logistic transformation function parameterized by the qualitative anchors. This provides a smooth and monotonic mapping from raw values to fuzzy scores.

$$\mu(x) = \frac{1}{1+\left(\dfrac{x-c}{f-c}\right)^{-k}} \quad (13)$$

Handling Exact Partial Membership (0.5): Cases with raw values exactly equal to T_{cross} would result in a membership of 0.5, creating logical ambiguity in the truth table analysis. Following standard fsQCA protocols (Ragin, 2008), we apply a minimal constant $\varepsilon = 0.001$ to shift these values, ensuring no case is dropped from the Boolean minimization analysis.

$$if\ \mu_{x,i} = 0.5, then\ \mu_{x,i} = 0.501 \quad (14)$$

This comprehensive mathematical calibration framework ensures that the resulting fuzzy sets (FMV, FTA, FFOD, FFOR, FPE) mathematically represent the qualitative degrees of user engagement rather than merely rank-ordering them. Where *f*, *c*, *n* are full membership, crossover, and full non-membership anchors. To overcome this problem, 0.5 was modified to 0.501 in the calibrated data.

4 Configuration Path Analysis

4.1 Analysis of Necessary Conditions

Before performing the configuration sufficiency condition test, a necessity test is performed on a single condition variable to verify whether there are necessary conditions in the condition variable that leads to the desired outcome. Necessity testing refers to the evaluation of whether a specific antecedent condition is a prerequisite for the occurrence of the outcome. If the consistency value of a particular antecedent condition is greater than 0.9, it can be considered necessary, as it indicates a strong subset relationship between the outcome and that antecedent conditio [32]. The adequacy test evaluates whether antecedent conditions are sufficient to cause the occurrence of results alone, and needs to consider both consistency and coverage to show the explanatory strength and empirical importance of the combination of antecedent conditions on the results [33]. This approach not only reveals complex causal relationships, but also provides important insights into which conditions affect outcomes and to what extent through consistency and coverage analysis, providing a theoretical basis for policy formulation and practice.

Table 5. Results of the necessity test of individual antecedents

Conditions	High-quality knowledge contribution	
	Consistency	Coverage
FMV	0.559892	0.603243
~FMV	0.658532	0.525116
FTA	0.611458	0.597501
~FTA	0.632108	0.545463
FFOD	0.586390	0.576409
~FFOD	0.652704	0.560312
FFOR	0.625304	0.622528
~FFOR	0.622668	0.528693
FPE	0.531361	0.577712
~FPE	0.708811	0.561461
PA	0.498885	0.465911
~PA	0.501115	0.450872

The results of the analysis of the necessary conditions for the data of this study using fsQCA 4.1 software are shown in Table 5. It can be seen that the consistency of the six antecedents is less than 0.9, so there is no absolute necessary condition for achieving high-quality knowledge contribution. The coverage showed that 45.09%-62.25% of cases (i.e., knowledge contributors) could explain that these conditions were not a single necessary condition for high-quality knowledge contribution. The explanation of the contribution of high-quality knowledge by a single influencing factor is weak. Therefore, it is necessary to explore the combination of influencing factors that drive high-quality knowledge contribution.

4.2 Conditional Configuration Analysis

In fsQCA, setting the appropriate consistency level and case frequency threshold is a key step to ensure the reliability and validity of the analysis results. First, the level of consistency reflects the degree to which the combination of conditions interprets the results. A higher level of agreement indicates a more significant correlation between the condition and the outcome. Most studies have shown that the level of agreement should be set at no less than 0.8 to ensure the reliability and scientificity of the analytical results [34]. Second, the case frequency threshold is used to filter rare configurations in the analysis to improve the stability and representativeness of the results. Determining the frequency threshold is one of the key steps in analyzing the impact of a combination of conditions on an outcome. Grechhamer et al. [35] noted that the frequency threshold should be set at a level that retains at least 80% of cases, and it is important to set an appropriate frequency threshold to ensure the stability of the analysis and the reproducibility of the results. For small and medium-sized samples (N<150), the frequency threshold is set to 1, and the frequency threshold for large samples should be increased accordingly to ensure that each condition combination contains at least two cases, so as to avoid the problem of unstable rare configurations caused by too few sample sizes.

PRI consistency is used to avoid simultaneous subset relations of configurations in both the outcome and the absence of the outcome (i.e., negation). PRI consistency scores should be high and close to raw consistency scores (e.g., 0.7), while configurations with PRI scores below 0.5 indicate significant inconsistency [36].

PRI consistency:

$$PRI(X) = \frac{\sum min(X_i, KCQ_i) - \sum_i min(X_i, 1 - KCQ_i)}{\sum min(X_i, KCQ_i)} \tag{15}$$

Thus, a *PRI* consistency threshold should also be used configurations with *PRI* scores below 0.5 indicate significant inconsistency.

To rigorously handle simultaneous subset relations—where a configuration might appear sufficient for both the outcome and its negation due to data noise—we employ the Proportional Reduction in Inconsistency (*PRI*) measure. As shown in the equation above, *PRI* imposes a stricter penalty on cases that are inconsistent (i.e., cases where membership in the configuration X is high, but membership in KCQ is low), by subtracting the intersection of the configuration with the negated outcome (KCQ) from both the numerator and denominator. Configurations with PRI scores below 0.5 are considered logically contradictory and are removed from the solution.

$$\mathrm{PRI} = \frac{\sum(\min(\mu x, \mu KCQ) - \min(\mu x, \mu KCQ\ ,\ \ \mu \sim KCQ)}{\sum(\mu x - \min(\mu x, \mu KCQ\ ,\ \ \mu \sim KCQ))} \tag{16}$$

Following the evaluation of individual configurations, the overall solution consistency and solution coverage are calculated to assess the sufficiency and empirical relevance of the complete set of configurations leading to the outcome. These metrics aggregate the performance of all sufficient paths identified in the analysis.

The overall solution consistency is calculated as:

$$Solution\ Consistency = \frac{\sum_{i=1}^{n} min(\mu solution_i, \mu KCQ_i)}{\sum_{i=1}^{n} (\mu solution_i)} \tag{17}$$

Here, μ $solution_i$ represents the membership of case i in the union of all sufficient configurations identified in the intermediate solution. It is computed as the maximum membership across these configurations:

μ $solution_i = \max(\mu X_{1i}, \mu X_{2i}, \ldots, \mu X_{ki})$, where $X_1 \ldots X_k$ are the sufficient configurations.

The overall solution coverage is calculated as:

$$Solution\ Coverage = \frac{\sum_{i=1}^{n} \min(\mu solution_i, \mu KCQ_i)}{\sum_{i=1}^{n} (\mu KCQ_i)} \tag{18}$$

Solution coverage indicates the proportion of the outcome membership that is explained by the combined set of sufficient paths.

In this study, fsQCA4.1 software was used to construct a truth table, the consistency threshold was set to 0.8, the case frequency threshold was set to 2, and the case results with initial consistency lower than 0.8 and PRI value lower than 0.5 were manually modified to 0. Based on the above analysis, the six antecedent conditions must interact synergistically to collectively produce high-quality outcomes in knowledge contribution. Therefore, it is essential to further investigate the synergistic effects of all antecedent conditions.

Intermediate solutions are generally superior to complex and simple solutions, so intermediate solutions are used to determine the number of configurations that lead to the results and the conditions that these configurations contain. The results of the parsimonious solution are used to determine the core conditions that are important for a given configuration. The condition of recurrence with the intermediate solution in the simple solution is the core condition of the given configuration, indicating that there is a strong causal relationship with the occurrence of the result, while the other conditions that appear in the intermediate solution but do not appear in the economical solution are the edge conditions, indicating that there is a weak causal relationship with the occurrence of the result.

The overall solution for achieving high-quality knowledge contribution can be expressed as the union of all sufficient configurations identified through fsQCA:

$$KCQ = \bigcup_{k=1}^{K} \bigcap_{j=1}^{J_k} X_{kj} \tag{19}$$

Here, K =10 represents the ten sufficient configurations identified in this study.

The intermediate solution reveals ten configurations that serve as sufficient conditions for high-quality knowledge contribution, representing the combinations of factors that drive improvements in knowledge contribution quality. The simplified solution identifies the core conditions within these combinations, as summarized in Table 6. The consistency of the ten solutions is 0.713056, with a coverage of 0.526583, indicating that 71.31% of the improvements in knowledge contribution quality are driven by combinations that satisfy these ten configurations, which collectively explain 52.66% of the sample cases of knowledge contributors.

Raw coverage refers to the proportion of cases among knowledge contributors that can be explained by a given combination of affordances. Unique coverage indicates the proportion of cases that can only be explained by that specific combination of affordances. Thus, raw coverage and unique coverage represent the explanatory power and uniqueness of the combinations in enhancing knowledge contribution quality, respectively. The consistency of each individual solution within the ten configurations exceeds 0.74, demonstrating a strong subset relationship between these configurations and successful outcomes, indicating that the antecedent conditions have a robust explanatory capacity for the outcome variable.

Table 6. Configuration of influencing factors of high-quality knowledge contribution behavior

Conditional configuration		Network-Association Driven			Metavoicing-Association Driven			Role-Association Driven		Triggered-Association Driven	
Affordance	Symbol	1	2	3	4	5	6	7	8	9	10
Metavoicing	FMV	●	●	○	●	●	●	◯	●		◯
Triggered attending	FTA		◯	◯			○			●	●
Network-informed associating	FFOD (Followed)	●	●	●	●		◯	◯	◯	●	◯
	FFOR (Follower)	●	●	●		●	●	●	○		●
Generative role-taking	FPE (Public editor)		•	◯	◯	◯	◯	●	◯	◯	
Generative role-taking	PA (Platform Arbitration)	◯		●	◯	◯		◯	●	◯	
Raw coverage		0.145774	0.197009	0.102469	0.153432	0.15371	0.194569	0.121309	0.145903	0.165299	0.24865
Unique coverage		0.00914907	0.0190436	0.0152483	0.0151806	0.0049541	0.00243974	0.0151129	0.0533287	0.0216933	0.0328009
Consistency coverage		0.791682	0.870359	0.8	0.759757	0.80914	0.824763	0.786814	0.797991	0.741368	0.790392
Solution coverage		0.526583									
Solution consistency		0.713056									
Typical knowledge contributor user name		Pansz, et al.	Zhao Ling, et al.	ze ran, et al .	Ling Chu, et al.	warfalcon, et al.	Tourist Research Association, et al.	Institute for Planets, et al.	blues, et al.	Shi Nian, et al.	Dancing, et al.

●• Indicates that the condition exists,

◯ ○ Indicates that the condition does not exist,

A space indicates that the condition may or may not exist.

● ◯ Represents the core condition,

•○ Represents an edge condition.

4.3 Analysis of Configuration Results

As shown in Table 6, the affordance factors of Network-informed Associating (Follower and Followed) and Metavoicing frequently appear, serving as core influencing factors for high-quality knowledge contributions across various configurations. In contrast, Triggered Attending and Generative Role-taking are identified as core influencing factors in only a few configurations. Based on the differing primary driving factors, the ten configurations are categorized into four types to analyze the specific driving paths of social media affordance on high-quality knowledge contributions: Network-Association Driven, Metavoicing-Association Driven, Role-Association Driven, and Triggered-Association Driven.

Network-Association Driven. To represent the interaction effects illustrated in the response surface plot (Fig. 2), we introduce a simplified interaction model linking metavoicing and followers to knowledge contribution quality:

$$KCQ = \beta_0 + \beta_1 FMV + \beta_2 FFOR + \beta_3 (FMV \times FFOR) \quad (20)$$

This parametric form supports the graphical interpretation of nonlinear joint effects presented in Fig. 2.

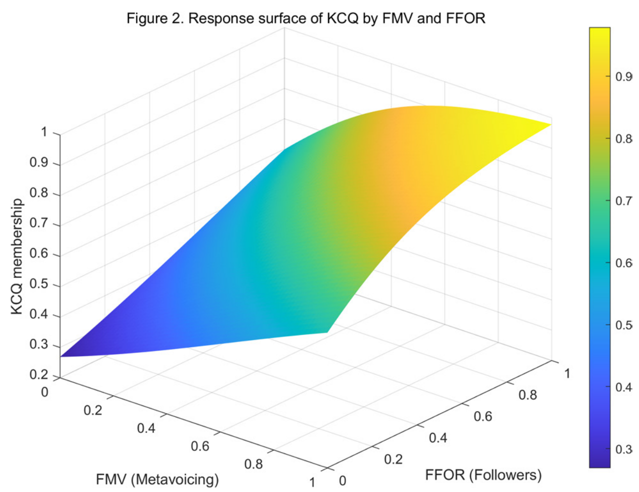

Fig. 2. KCQ response surface

The Fig. 2 shows how Metavoicing and Followers jointly shape KCQ membership, using a nonlinear interaction. In the graph, the vertical axis represents the fuzzy membership degree of Knowledge Contribution Quality (KCQ), and the horizontal axis represents the membership degree of Metavoice and Number of Followers (NPO). The closer the color is to yellow, the higher the membership degree of KCQ. The curve generally shows a monotonically increasing trend, indicating a positive interaction: when FMO is high, increasing FMV has a more significant impact on KCQ; and vice versa. The slight curvature of the curve also suggests diminishing marginal returns: when both are already high, further increasing either one will slow down the growth of KCQ. Configuration 1 (FMV*FFOD*FFOR*~PA): Network-informed Associating (Followed and Follower) and Metavoicing serve as core conditions in driving high-quality knowledge contributions. The Network-informed Associating and Metavoicing affordances enable knowledge contributors to overcome the limitations posed by the absence of Generative Role-taking (Platform Arbitration). The consistency of Configuration 1 is 0.791682, with an original coverage of 0.145774 and a unique coverage of 0.00914907. This indicates that this configuration path can explain 14.58% of high-quality knowledge contribution cases, and approximately 0.91% of the cases can be uniquely explained by this specific configuration path.

Configuration 2 (FMV*~FTA*FFOD*FFOR*FPE) Network-informed Associating (Followed and Follower) and Metavoicing affordances serve as core conditions in driving high-quality knowledge contributions. This means that Network-informed Associating, Metavoicing, and Generative Role-taking (Public Editor) affordances enable knowledge contributors to overcome the limitations posed by the absence of Triggered Attending. The consistency of Configuration 2 is 0.870359, with an original coverage of 0.197009 and a unique coverage of 0.0190436. This indicates that this configuration path can explain 19.7% of high-quality knowledge contribution cases, and approximately 1.9% of the cases can be uniquely explained by this specific configuration path.

Configuration 3 (~FMV*~FTA*FFOD*FFOR*~FPE*PA) Network-informed Associating (Followed and Follower) and Generative Role-taking (Platform Arbitration) affordances serve as core conditions in driving high-quality knowledge contributions. This means that Network-informed Associating and Generative Role-taking (Platform Arbitration) affordances enable knowledge contributors to overcome the limitations posed by the absence of Triggered Attending, Generative Role-taking (Public Editor), and Metavoicing. The consistency of Configuration 3 is 0.8, with an original coverage of 0.102469 and a unique coverage of 0.0152483. This indicates that this configuration path can explain 10.25% of high-quality knowledge contribution cases, and approximately 1.52% of the cases can be uniquely explained by this specific configuration path.

This type emphasizes the importance of Network-informed Associating and Metavoicing in high-quality knowledge contributions. Literature indicates that the dissemination and reception of information within social networks play a crucial role in facilitating knowledge sharing. This network association not only enhances the accessibility of information but also fosters interaction among users. By cultivating positive network relationships, knowledge contributors can overcome role limitations on the platform, thereby increasing both the quality and quantity of their contributions. In virtual communities, encouraging users to establish broader networks of attention and actively participate in discussions can effectively enhance the quality of knowledge contributions. Platforms can utilize algorithmic recommendation mechanisms to prioritize the display of high-quality content, thereby promoting users' network associations and Metavoicing.

Metavoicing-Association Driven. Configuration 4 (FMV*FFOD*~FPE*~PA): Metavoicing and Network-informed Associating (Followed) are core conditions when driving high-quality knowledge contributions. The affordances of Metavoicing and Network-informed Associating can help knowledge contributors overcome the limitations posed by insufficient Generative Role-taking and Mediatory Engagement. The consistency of Configuration 4 is 0.759757, with an original coverage of 0.153432 and a unique coverage of 0.0151806, indicating that this configuration path can explain 15.34% of the high-quality knowledge contribution cases, with approximately 1.5% of cases being uniquely explained by this path.

Configuration 5 (FMV*FFOR*~FPE*~PA): Metavoicing and Network-informed Associating (Followers) are core conditions when driving high-quality knowledge contributions. The affordances of Metavoicing and Network-informed Associating (Followers) can help knowledge contributors overcome the limitations posed by insufficient Generative Role-taking and Mediatory Engagement. The consistency of Configuration 5 is 0.80914, with an original coverage of 0.15371 and a unique coverage of 0.0049541, indicating that this configuration path can explain 15.37% of the high-quality knowledge contribution cases, with approximately 0.5% of cases being uniquely explained by this path.

Configuration 6 (FMV*~FTA*~FFOD*FFOR*~FPE): Metavoicing and Network-informed Associating (Followers) are core conditions in driving high-quality knowledge contributions. The affordances of Metavoicing and Network-informed Associating (Followers) can assist knowledge contributors in overcoming the limitations imposed by insufficient Followed content, Public Editing, and Triggered Attending. The consistency of Configuration 6 is 0.824763, with an original coverage of 0.194569 and a unique coverage of 0.00243974, indicating that this configuration path can explain 19.46% of high-quality knowledge contribution cases, with approximately 0.24% of cases being uniquely explained by this path.

In this context, the presence of Metavoicing and Followers is a crucial condition for driving high-quality knowledge contributions. Research indicates that Metavoicing can help individuals establish credibility on social media, thereby increasing the effectiveness of their knowledge contributions. The active participation of Followers can also provide support and feedback for knowledge contributors, fostering positive interaction. Virtual communities should focus on cultivating users' Metavoicing abilities by encouraging proactive engagement through training and incentive mechanisms. Additionally, platforms can provide users with tools to better manage and interact with their Followers, thereby enhancing the quality of knowledge contributions.

Role-Association Driven. Configuration 7 (~FMV*~FFOD*FFOR*FPE*~PA): Followers and Public Editors are core conditions in driving high-quality knowledge contributions. This indicates that the affordances of Followers and Public Editors can help knowledge contributors overcome the constraints posed by the insufficient affordances of Metavoicing, Followed, and Generative Role-taking. The consistency of Configuration 7 is

0.786814, with an original coverage of 0.121309 and a unique coverage of 0.0151129, suggesting that this configuration path can explain 12.13% of the high-quality knowledge contribution cases, with approximately 1.51% of cases uniquely explained by this configuration.

Configuration 8 (FMV*~FFOD*~FFOR*~FPE*PA): Metavoicing and Generative Role-taking are core conditions in driving high-quality knowledge contributions. This suggests that the affordances of Metavoicing and Generative Role-taking can assist knowledge contributors in overcoming the constraints posed by the insufficient affordances of Followed, Followers, and Public Editors. The consistency of Configuration 8 is 0.797991, with an original coverage of 0.145903 and a unique coverage of 0.0533287, indicating that this configuration path can explain 14.59% of the high-quality knowledge contribution cases, with approximately 5.33% of cases uniquely explained by this configuration.

In this context, Generative Role-taking occupies a central role in promoting high-quality knowledge contributions. Literature suggests that the diversity and flexibility of roles are key factors in fostering innovation and knowledge sharing. By participating in multiple roles, users can contribute knowledge from different perspectives, thereby enhancing the overall quality of contributions. Encouraging users to adopt multiple roles on the platform can be achieved by implementing role labels and tasks. Additionally, the platform can organize activities to facilitate role interaction among users, thereby enriching the diversity of knowledge contributions.

Triggered-Association Driven. The Fig. 3 visualizes the sufficiency consistency Cons across all 16 binary configurations of four conditions. Configuration 9 (FTA*FFOD*~FPE*~PA): Triggered Attending and Following are core conditions in driving high-quality knowledge contributions. The affordances of Triggered Attending and Following can help knowledge contributors overcome the limitations posed by insufficient Public Editing and Mediating Participation. The consistency of Configuration 9 is 0.741368, with an original coverage of 0.165299 and a unique coverage of 0.0216933, indicating that this configurational path can explain 16.53% of high-quality knowledge contribution cases, with approximately 2.17% of cases being exclusively explained by this path.

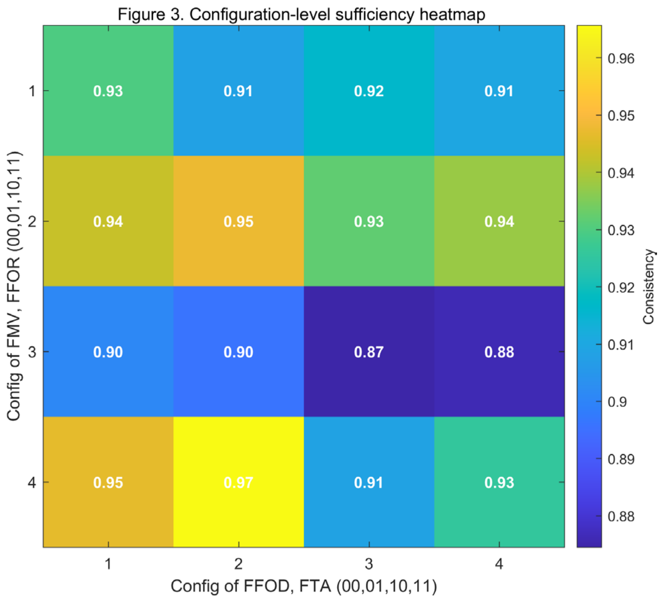

Fig. 3. Configuration-level sufficiency heatmap

Configuration 10 (~FMV*FTA*~FFOD*FFOR): Triggered Attending and Followers are core conditions in driving high-quality knowledge contributions. The affordances of Triggered Attending and Followers can help knowledge contributors overcome the limitations posed by insufficient Metavoicing and Following. The consistency of Configuration 10 is 0.790392, with an original coverage of 0.24865 and a unique coverage of 0.0328009, indicating that this configurational path can explain 24.87% of high-quality knowledge contribution cases, with approximately 3.28% of cases being exclusively explained by this path.

This type emphasizes the importance of Triggered Attending. The literature indicates that Triggered Attending can quickly stimulate user engagement, enhancing their motivation for knowledge contribution. This approach is particularly well-suited for the dynamic environment of social media, as it allows for timely responses to users' interests and needs. Virtual communities should design real-time feedback mechanisms to stimulate users' Triggered Attending. Additionally, regular online events or challenges can be organized to motivate users to participate in discussions and sharing, thereby improving the overall quality of knowledge contributions.

4.4 Robustness Test

In this paper, the robustness test of the antecedent configuration of high-quality knowledge contribution is carried out by adjusting the case frequency threshold and the original consistency. First, by increasing the case frequency threshold from 2 to 3, the intermediate solution produces 10 configurations that are largely consistent with the existing solutions; overall consistency decreases from 0.713056 to 0.715946, while overall coverage declines from 0.526583 to 0.460988. Second, when the original consistency is raised from 0.80 to 0.85, there is no substantive change in the resulting configurations, and both overall consistency and coverage remain largely unaffected. Given the relatively large sample size, these results indicate that the configurations presented in this study exhibit strong robustness.

5 Conclusion and Discussion

This study provides a comprehensive analysis of the conditions and configurations driving high-quality knowledge contribution in virtual communities, particularly within the realm of social media. Employing fuzzy-set qualitative comparative analysis (fsQCA), the findings reveal that high-quality knowledge contributions are not determined by single necessary conditions but rather emerge from specific combinations of antecedent factors.

The findings reveal that configurations characterized by the presence of Network-informed associating consistently demonstrate a high explanatory power for knowledge contributions, supporting the notion that strong ties in social networks enhance the dissemination and reception of information. This aligns with prior literature suggesting that users who actively engage in building their social networks are better positioned to contribute valuable knowledge, as their enhanced accessibility to diverse information sources facilitates knowledge sharing.

Moreover, the significance of Metavoicing emerges as a crucial driver of knowledge contributions, reflecting its role in establishing credibility and fostering interactive engagement among users. The presence of followers and active engagement in metavoicing not only increases the perceived value of knowledge contributions but also reinforces community trust and reciprocity. This highlights the need for virtual communities to cultivate metavoicing capabilities among users, fostering environments conducive to collaborative knowledge sharing.

Additionally, the configurations suggest that while Generative role-taking and Triggered attending play supplementary roles in specific contexts, their influence is overshadowed by the more dominant affordances of network association and metavoicing. This finding contributes to the ongoing discourse regarding the interplay between user roles and knowledge dynamics in digital spaces.

In terms of practical implications, the results advocate for social media platforms to leverage algorithmic recommendations that prioritize high-quality content and encourage the establishment of expansive networks among users. By fostering environments that support metavoicing and active participation, platforms can significantly enhance the quality and quantity of knowledge contributions. The findings not only contribute to the theoretical understanding of knowledge dynamics in virtual communities but also offer actionable insights for practitioners seeking to enhance knowledge sharing on digital platforms.

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