Research article

The quality of crowdsourcing virtual community and users' voice behavior: An analysis of stimulus-organism-response framework among Chinese users

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A B S T R A C T

The quality of a crowdsourcing virtual community is an essential factor that stimulates users' perceptions of belonging and attachment to the community, thereby influencing their behavior. As a prerequisite for the development of "creative crowdsourcing," it is particularly important to study how users' voice behavior can be promoted in virtual communities. Drawing on the Stimulus-Organism-Response (SOR) framework and the Social Identification Theory, this study developed a conceptual model that investigates the impact of crowdsourcing virtual communities in system, information, interaction, and service quality on users' voice behavior. Furthermore, we introduce community identification and self-disclosure to further analyze the influencing mechanism between these two variables. Data were collected through 672 survey questionnaires from participants in well-known crowdsourcing virtual communities such as Xiaohongshu, Bilibili, Haier Hope, Test Baidu, and Test China. Using hierarchical regression and bootstrap analysis, we found a positive correlation between the quality of the crowdsourcing virtual community and users' voice behavior, with community identification acting as a mediator. Furthermore, self-disclosure showed a significant moderating effect on the relationship between community identification and voice behavior. These findings significantly contribute to the theoretical landscape by advancing the SOR framework within a virtual community. This not only deepens the understanding of the quality of the crowdsourcing virtual community, but also provides theoretical and practical implications for managers and users on how to promote voice behavior.

1. Introduction

In the era of mobile Internet, the traditional social barriers between users and companies, as well as among users are gradually dissipating [1]. Users actively participate in various online platforms for communication and interaction, among which, crowdsourcing virtual communities have emerged as a vital bridge connecting users with organizations [2–5]. Crowdsourcing virtual communities, such as the China Software Developer Network (CSDN) and Task China (Task CN), have initiated discussions within the community, fostering the exchange of knowledge and resources and harnessing collective wisdom to address challenges. Other communities, such as Bilibili, Meitu, and Honor of Kings, have strategically shifted their product planning and selection to actively

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engage with the community of users. This not only captures innovative ideas from the public, but also aligns more closely with users' preferences and dynamic needs, thereby significantly mitigating the R&D and marketing risks.

Crowdsourcing virtual communities can reduce communication costs and have become a crucial means of enhancing users experience [6,7]. They provide users with more convenient feedback channels [8,9]; moreover, the feedback submitted by users has evolved into a crucial factor that influences the enterprise development [10]. Therefore, researchers have focused on enhancing the quality of crowdsourcing virtual communities [11,12]. It involves a comprehensive assessment of the community system, information, services, and interactions [13–15]. By optimizing these key dimensions, a community can better meet users needs, thereby enhancing users' sense of participation and satisfaction [16,17]. For example, considerable research indicates that the quality of virtual communities is a significant factor influencing users' attitudes and behaviors, such as the perceived benefits of the virtual community, customer satisfaction, and member loyalty [14,16,18–20]. However, previous studies have primarily focused on the impact of community quality on the willingness or motivation of users to invest resources (e.g., time and energy) in engaging in activities such as knowledge sharing, innovation behavior [21–23], and participation within virtual communities [24,25]. Additionally, these studies emphasize the impact mechanisms of relevant factors in virtual brand communities (e.g., Xiaomi Community and Huawei Community) and social networks (e.g., Facebook, Twitter, WeChat and Weibo) on users' psychology and how they generate knowledge contributions [26–28]. There is limited research that deeply analyzes another type of virtual community quality, namely, the crowdsourcing virtual community, especially whether the quality of virtual crowdsourcing communities can influence the likelihood of users proposing suggestions and opinions.

Individual voice behaviors involve contributing to and sharing their knowledge and experiences [29–31], representing active participation in social activities [32]. Many studies have investigated employee voice behavior and its antecedents in organizational settings, such as job satisfaction, leadership styles, and organizational culture [33–35]. Scholars have proposed that employee voice behavior is crucial for organizational development as it provides valuable information that aids in improving products or services. In virtual communities, users' voice behavior is characterized as an out-of-role interpersonal communication behavior in which users articulate their thoughts, opinions, and suggestions regarding a community's products or services [36]. With the proliferation of digital platforms, the channels for users' voice behavior have become more diverse [37,38]. Social media, online forums, user reviews, and similar functions have emerged as pivotal spaces for users to express their opinions and offer businesses broader and more real-time feedback of user opinions [39]. Crowdsourcing virtual communities, which are distinct from other virtual communities in their user demographics, interaction patterns, and information dissemination methods, have rendered users' voice behavior an indispensable element in the "crowdsourcing of creativity" [40–42]. This behavior acts as a significant catalyst for fostering business innovation, service enhancement, and risk alertness [43]. Despite the existing research exploring the relationship between community quality and user engagement, the specific dynamics between community quality and users' voice behavior in virtual crowdsourcing communities remain insufficiently investigated. Therefore, this study aims to conduct an in-depth examination of the relationship between community quality and users' voice behavior in virtual crowdsourcing communities, with the potential to unveil the motives and patterns underlying user participation in these environments.

Based on this, this study employs the Stimulus-Organism-Response (SOR) framework to address these aims [44]. According to the SOR model, specific environmental features trigger an individual's cognitive and emotional states, subsequently driving distinct behavioral responses. Here, the quality of crowdsourcing virtual community is defined as the "stimulus," while users' voice behavior is recognized as diverse behavior in response to the community's performance in system, information, service and interaction, hence labeled as the "response." Additionally, the quality of crowdsourcing virtual community, as an external environmental factor, instigates a sense of belonging and attachment in users, thereby influencing their identification with the community [45,46]. With a heightened sense of community identification, users are more inclined to engage in supportive behaviors, such as providing feedback and suggestions and promoting community citizenship behaviors [47,48]. Thus, drawing from Social Identification Theory [49], this study integrates community identification as the "organism" in the SOR framework [50], indicating that the quality of crowdsourcing virtual community could impact users' voice behavior through community identification. Moreover, researches has shown that personal characteristics significantly affect emotion, cognition, and behavior [51–53]. Therefore, this study also introduces the personality trait of self-disclosure, which is an intrinsic motivating factor for individual behavior [54,55]. Users with strong self-disclosure may be more likely to transform their sense of community identification into external behaviors, thus generating more voice behavior [56]. Therefore, this study further explores the moderating effect of self-disclosure on the relationship between community identification and users' voice behavior.

To sum up, this study makes three major contributions to the literature. First, it investigates the relationship between the quality of a crowdsourcing virtual community, consisting of system quality, information quality, service quality, interaction quality, and users' voice behavior. It offers valuable insights for both the areas of crowdsourcing virtual communities and individual voice behavior. Second, drawing on the SOR model, we developed a "crowdsourcing virtual communities quality (S)–community identification (O)–users' voice behavior (R)" model to examine the mediating effect of community identification, which helps us better understand the relationships between these variables. Third, this study introduces self-disclosure as a moderator between community identification and users' voice behavior, thereby contributing to the existing body of research on the impact of personality on users' voice behavior. By conducting an in-depth investigation into the relationship between the quality of crowdsourcing virtual communities and users' voice behaviors, we aimed to unveil the motives and patterns of user engagement within these communities. This study proposes providing more specific guidance for optimizing the operations and user experience of crowdsourcing virtual communities. Not only does this study seek to address theoretical gaps but it also contributes to enhancing the competitive advantage of crowdsourcing virtual communities.

2. Theory and hypotheses

2.1. The quality of crowdsourcing virtual community and users' voice behavior

A crowdsourcing virtual community is a virtual platform established by enterprises, involving many voluntary users engaged in mutual knowledge sharing, communication, and interactions to explore ideas and accomplish innovative tasks [57]. In alignment with the definition and dimensions of virtual community quality by the scholars [13,18,58], this study defines the quality of a crowdsourcing virtual community as the overall evaluation made by users within the community to fulfill their individual needs. This evaluation includes four dimensions: system quality, information quality, service quality, and interaction quality. System quality refers to system characteristics such as the performance, convenience, security, stability, and aesthetics of the network carrier to which the community is attached [13,21,59]. Information quality refers to the authenticity, effectiveness, richness, and timeliness of the information provided by a crowdsourcing virtual community [60]. Service quality is a comprehensive evaluation of the efficiency and effectiveness of the services delivered through the crowdsourcing virtual community website. Finally, the interaction quality measures the extent of information communication and emotional interaction among users and between users and the platform [61,62]. Given escalating user demand for virtual community quality, scholars have investigated the quality and outcomes of crowdsourcing virtual communities. For example, Martinez [63] and Kohler & Chesbrough [64] explored the quality of system design, focusing on optimizing system operation, information, and interaction qualities. Rui and Ma [65] investigated the dimensions of users' perceived service quality, ease of use, and usefulness, and their impact on users' knowledge search behavior and knowledge contribution behavior.

Users' voice behavior involves users expressing their thoughts, opinions, and suggestions regarding products or services through out-of-role interpersonal communication [29,30]. Research on users' voice behavior has mainly focused on the antecedents. For example, Frey and Schneider [66] proposed that a set of strategies and techniques for online communities could enhance participants' effective voices. Empirical evidence by Sun et al. [36] confirms that customers' intrinsic motivation to voice facilitates their continuous voice intention of the virtual brand community. Additionally, Yang et al. [37] established a positive association between online brand community experience and customer voice. Their studies showed that community engagement acted as a mediating factor, whereas, community commitment functioned as a moderating factor.

This study posits that a high-quality crowdsourcing virtual community can enhance users' voice behavior in three ways. First, the quality of the virtual community system, information, service, and interaction can be regarded as benefits that customers receive from the community [13,16,59], which positively affects the quality of the relationship between customers and the community [67,68]. In response, customers will engage in behaviors that include sharing information actively in the community, participating in new product development, contributing to technological improvement, and providing product feedback [67–70]. These behaviors can be regarded as users' voice behavior. Second, studies have shown that information usefulness, website design, perceived value, and service quality have a positive impact on users' satisfaction [71,72]. This satisfaction also fosters a connection between users and the community, prompting users to be more willing to provide suggestions and advise aimed at enhancing community quality. Third, the quality of community interaction assists users in perceiving functional, familiar, similar, and symbolic experiences, thereby enhancing their interpersonal attraction and influence. Consequently, this quality strengthens users' loyalty and fosters the exchange of product information, ultimately facilitating the exchange of innovative ideas [57,61,73]. In summary, a high-quality crowdsourcing virtual community provides users with a secure, stable, aesthetically pleasing, and user-friendly platform. It offers authentic, effective, rich, timely, and high-value information along with efficient, high-quality personalized services and a platform for information communication and emotional interaction. This comprehensive approach fosters trust among users, encouraging them to actively propose valuable suggestions and solutions for the improvement of products and services, thereby leading to users' voice behavior. Hence, we propose the following.

Hypothesis 1.   The quality of a crowdsourcing virtual community is positively associated with users' voice behavior. In other words, the system, information, service, and interaction quality of the crowdsourcing virtual community are positively related to users' voice behavior.

2.2. Mediating effect of community identification

The concept of community identification originates from the application of the Social Identification Theory in a community context. This refers to the extent to which community users attribute themselves to the community, with members exhibiting a high degree of recognition of its traditions, goals, and norms. This encompasses both cognitive and affective dimensions of identity [45–48, 74]. Previous studies showed that the strength of a user's community identification is positively correlated with their emotional reliance on and sense of belonging to the community, thus influencing customers' behavior [75–78].

According to the SOR model, specific environmental attributes act as stimuli that influence an individual's cognitive and emotional states, which in turn drive behavioral responses. In this study, the quality of crowdsourcing virtual community can be regarded as the "stimulus," the community identification functions as the "organism," and the users' voice behavior as the "response." As external environmental factors, the quality of the system, information, service, and interaction with crowdsourcing virtual communities trigger a sense of belonging and attachment to the community, thereby influencing users' cognitive perception and emotional attachment [45, 79,80]. This further impacts the community's user identification. More specifically, in crowdsourcing virtual communities with high system quality, information architecture significantly enhances the user experience [79]. A well-designed navigation system facilitates optimal information access, and an aesthetically pleasing interface design enhances perceptual experiences. The efficiency and

effectiveness of the services provided are superior [79]. E-service quality reflects users' relationship-specific experiences [81]. Positive experiences foster emotional attachment to the community [82], increasing users' community identification [83]. Furthermore, crowdsourcing virtual communities with high information quality offer users real, effective, rich, interesting, and timely information. Users derive a strong sense of value from such information [84], which helps them form an identity and attachment to the community. This encourages users to become community members and establishes a sense of community identification [85,86]. Finally, interaction quality features robust interactions among users and a high level of community activity. This continuous interaction leads to the establishment of shared values and preferences within the community, fostering interpersonal trust through exchanges, thereby reinforcing community identification [57,73,74]. Thus, this study proposes that the quality of system, information, service, and interaction within crowdsourcing virtual communities are crucial predictors of community identification.

Based on Social Identification Theory, a robust sense of community identification among users of crowdsourcing virtual communities promotes a feeling of belonging and emotional reliance on the community. Consequently, individuals invest more in a community's future development and perceive contributing to the community as directly benefiting themselves [87]. This sense of dedication motivates them to actively support their community, thereby engaging in voice behaviors [88]. Previous studies have confirmed that organizational identification significantly affects individuals' voice behavior [89,90]. For example, Fuller et al. [91] emphasized that in organizational settings, an individual's identification generates a sense of responsibility and motivates actions, such as voice behavior, to enhance organizational effectiveness. In virtual communities, researchers have proposed that users' identification with social networking sites (SNS) prompts citizenship behavior and encourages active participation in product evaluations and creative contributions in virtual communities [92]. This further promotes voice behaviors [36,93]. Hence, we propose the following.

Hypothesis 2. Community identification mediates the relationship between the quality of a crowdsourcing virtual community and users' voice behavior.

2.3. Moderating effect of self-disclosure

Self-disclosure is a personality trait wherein individuals utilize various means to convey information to others, maintain communication, or fulfill personal needs [54,55]. Scholars have extensively investigated the influence of self-disclosure on interpersonal relationships, as well as its implications for emotions and behaviors in social interactions [94,95]. For example, Lin and Utz [96] found that users who frequently share their feelings, thoughts, and experiences on SNS (i.e., they have high self-disclosure) can increase feelings of familiarity and closeness. This heightened self-disclosure further fosters social attraction [97].

This study proposes that self-disclosure has a moderating effect on the relationship between community identification and users' voice behavior. In fact, the user's voice behavior on a virtual community implies strong individual psychological motivation, which is highly subjective and context-dependent. Individual characteristics have been found to significantly shape the inclinations, competencies, and knowledge essential for effective engagement within a social setting, and are closely linked to voice behavior [56]. An essential individual trait is self-disclosure, which serves as an intrinsic motivator of user behavior. This entails users sharing their thoughts, feelings, and experiences with others, reflecting their emphasis on self-expression within the virtual community and during interactions [98]. When users' self-disclosure is higher, they become more inclined to translate their psychological emotions, including feelings of dependence, belonging, and identification within the community, into practical expressions [94–97,99]. This inclination also leads them to be more proactive and spontaneous in expressing their opinions on community products, services, and management [100]. In other words, for users within crowdsourcing virtual communities characterized by higher self-disclosure, community
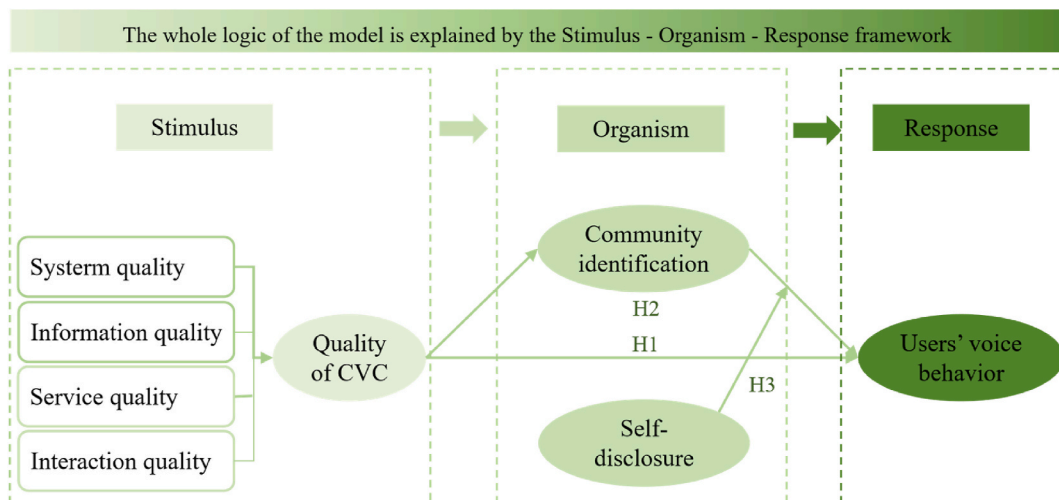

Fig. 1. Theoretical model (CVC = crowdsourcing virtual community).

identification exerts a more significant influence on their voice behavior. Thus, we propose the following.

Hypothesis 3.   Self-disclosure moderates the relationship between community identification and users' voice behavior.

The theoretical model is shown in Fig. 1.

3. Methods

3.1. Data collection and sample description

We employed a snowball sampling approach to disseminate questionnaires through diverse channels, including web links, emails, and mobile applications. Acknowledging the potential impact of participants' comprehension of crowdsourcing virtual communities, we integrated specific measures into the survey process. First, the initial question in the survey pertained to whether participants had been using crowdsourcing virtual communities, such as Xiaohongshu, Bilibili, Jianying, Qingyan Camera, Task CN, Haier Hope, Test Baidu, Wangzhe Camp, and CSDN, for a period exceeding one year. If the response was negative, the survey was closed automatically. This criterion served as a foundational element to ensure a certain level of familiarity with the communities and their dynamics. Second, before completing the questionnaire, participants received detailed information on the purpose of the study, the communities in question, and any relevant operational dynamics. This was aimed at establishing a baseline understanding among participants. Moreover, the survey instrument included explicit instructions and guidance on responding to community-specific aspects, thus reducing the likelihood of misinterpretation and ensuring standardized interpretations across participants. Throughout survey administration, we maintained open lines of communication, encouraging participants to seek clarification on community-related questions.

By combining the snowball sampling method with these measures to address the participants' understanding, we aimed to create a robust and informed sample. These steps reflect our commitment to mitigate the impact of platform dynamics on responses and ensure a comprehensive understanding of participant engagement in virtual communities. Ultimately, 1200 questionnaires were distributed. In total, 883 completed questionnaires were collected between May 2023 and January 2024. After eliminating 211 questionnaires that were considered invalid owing to a missing rate exceeding 10% and a repetition rate above 90%, 672 valid samples were obtained, achieving a recovery rate of 76.1%.

The demographic information of the 672 participants in the crowdsourcing virtual community was as follows. Females constituted a slightly higher percentage (53.27%) than males (46.73%). Regarding age groups, 12.95% of users were under 18 years old, 50.15% were 18–25 years old, 29.46% were 26–35 years old, 5.80% were 36–45 years old, and 1.64% were over 45 years old. Regarding education level, 31.10% had an education level of senior high school or below, 20.83% had junior college education, 34.82% had an undergraduate degree, 10.86% had a master's degree, and 2.38% had a doctoral degree. In terms of occupation, 51.49% were students, 30.80% were enterprise employees, 5.51% were civil servants, 7.74% were freelancers, and 4.46% were categorized as "other". Regarding monthly income, 16.22% of users earned under 1000 RMB, 22.92% earned 1000–5000 RMB, 24.11% earned 5000–8000 RMB, 23.51% earned 8000–10,000 RMB, and 13.24% earned over 10,000 RMB. In addition, the most commonly used crowdsourcing virtual community among the participants was Xiaohongshu (34.67%), followed by Bilibili (15.03%), Wangzhe Camp (13.54%), Qingyan Camera (9.97%), Jianying (9.67%), CSDN (7.59%), Task CN (4.32%), Test Baidu (2.83%), and Haier Hope (2.38%).

3.2. Measures

To ensure reliability and validity of the sample, the scales used in this study were sourced from reputable academic journals. All scales were originally presented in English and underwent meticulous adaptation into Chinese through a process of double-blind translation, with the assistance of English professionals and management professors. The Chinese version of the questionnaire underwent stringent modifications and verification to ensure accuracy. This study used the Likert 5-point scale, where responses ranged from "1 = strongly disagree" to "5 = strongly agree" for variable measurement.

Quality of crowdsourcing virtual community. The scale includes four dimensions. System, information, and service qualities were measured using Hsu et al.'s [59] scales. System quality included five items (e.g., "The interface design of this community is simple and clear"). Information quality was measured using a four-item scale (e.g., "The information provided by this community is accurate"). Service quality was measured using a five-item scale (e.g., "The community delivers the service exactly as promised"). Moreover, interaction quality was measured using Kang et al.'s [62] three-item scale (e.g., "Other members in this community react to my opinion and questions in a speedy manner"). The Cronbach's α for each dimension were 0.896, 0.872, 0.885, and 0.849, respectively.

Community identification. This study used a five-item scale developed by Algesheim et al. [74] for community identification. Sample items include "I consider myself part of this community". The Cronbach's α of this scale was 0.886.

Users' voice behavior. Liang et al.'s [101] five-item scale was used to assess users' voice behavior. This scale includes items such as "I will make suggestions that will benefit this community business for marketing purposes". The Cronbach's α for this scale was 0.889.

Self-disclosure. This scale was measured based on the research of Krasnova et al. [102] and Shih et al. [103], with a total of five items. Sample items include "When I have something to say, I like to share it on social media." The Cronbach's α for this scale was 0.891.

Controlled variables. Previous studies [51–53,104] have indicated that demographic variables and different virtual communities

can influence user attitudes and behaviors. Therefore, to avoid the impact of these variables on the proposed hypotheses, gender, age, education level, occupation, monthly income, different communities, and community update frequencies were chosen as controlled variables.

3.3. Data analysis

In this study, the data were analyzed using AMOS 26.0 and SPSS 26.0. First, to ensure construct reliability and convergence validity of all variables, initial tests for reliability and validity, including Cronbach's α, construct reliability (C.R.), average variance extracted (AVE) and standardized factor loadings were conducted. Second, descriptive analyses involving means and standard deviations as well as Pearson's correlation analysis were performed. Third, confirmatory factor analysis (CFA) was used to test the measurement model. A multicollinearity test and a one-way analysis of variance (ANOVA) were performed to ensure the accuracy of the proposed model. Finally, the hypotheses were tested using hierarchical regression and bootstrap analyses.

4. Results

4.1. Reliability and validity analysis

The Cronbach's α, C.R., AVE and standardized factor loading were used to test the reliability and validity of all variables. As shown in Table 1, the Cronbach's α values were above 0.8 ($\geq$0.7), C.R. values were above 0.8 ($\geq$0.7), and AVE values were above 0.6 ($\geq$0.5). The results indicated that the extraction degree of the measurement indicators within the factor was excellent, and all questions for each latent variable could consistently explain the latent variable. These findings demonstrated that all variables exhibited good

Table 1
The results of reliability and validity analysis.

Variables	Items	Standardized factor loading	S.E.
System quality	A1: The interface design of this community is simple and clear	0.939***	–
Cronbach's α =	A2: The interface design of this community enables me to get on to it quickly	0.732***	0.026
0.896	A3: The interface design of this community can be adapted to meeting my various needs	0.792***	0.024
C.R. = 0.905	A4: The community performs reliably	0.756***	0.025
AVE = 0.664	A5: The community makes it easy to get the information I need	0.760***	0.026
Information quality	B1: The community produces the most current information	0.928***	–
Cronbach's α =	B2: The information provided by this community is accurate	0.758***	0.029
0.872	B3: The community provides me with comprehensive information	0.725***	0.029
C.R. = 0.883	B4: The community provides me with all the information I need	0.770***	0.028
AVE = 0.663			
Service quality	C1: The community understands and address my needs	0.941***	–
Cronbach's α =	C2: The community delivers the service exactly as promised	0.745***	0.027
0.885	C3: The community provides me with personalized service	0.737***	0.026
C.R. = 0.894	C4: I can speak with a representative of the community in case I have problems	0.739***	0.027
AVE = 0.638	C5: The community is prompt in responding to my queries.	0.733***	0.027
Interaction quality	D1: I often immediately response to others' inquiries in this community	0.936***	–
Cronbach's α =	D2: Other member reacts to my opinion and questions in a speedy manner	0.743***	0.030
0.849	D3: Other member sends appropriate responses to my inquires	0.762***	0.031
C.R. = 0.872			
AVE = 0.706			
Community	F1: I am very attached to the community	0.908***	–
identification	F2: I consider myself part of this community	0.739***	0.028
Cronbach's α =	F3: Other community members and I share the same objectives	0.731***	0.029
0.886	F4: If community members planned something, I'd think of it as something "we" would do rather than something "they" would do	0.751***	0.028
C.R. = 0.893			
AVE = 0.634	F5: The friendships I have with other community members mean a lot to me	0.775***	0.029
Users' voice behavior	G1: I will proactively voice out constructive suggestions that help the community enterprise improve product quality and service	0.918***	–
Cronbach's α =			
0.889	G2: I will inform this community about problems I have encountered in using the product or receiving the service	0.756***	0.027
C.R. = 0.897			
AVE = 0.644	G3: I will proactively develop and make suggestions for issues that may hinder community management and development	0.743***	0.027
	G4: I will make constructive suggestions to improve the operation and management of this community	0.743***	0.027
	G5: I will make suggestions that will benefit this community business for marketing purposes	0.765***	0.028
Self-disclosure	K1: When I have something to say, I like to share it on social media	0.911***	–
Cronbach's α =	K2: I find time to keep my profile up-to-date on social media	0.748***	0.027
0.891	K3: I keep my friends updated about what is going on in my life through social media	0.758***	0.027
C.R. = 0.899	K4: I disclose personal preference on social media	0.780***	0.027
AVE = 0.648	K5: I have a comprehensive profile on social media	0.748***	0.028

Note: ***p < 0.001.

reliability and validity [105]. Moreover, the standardized factor loading of each item was greater than 0.6 and highly significant, indicating that the convergence validity of the variables was good.

4.2. Descriptive analysis

The means, standard deviation, and Pearson's correlation coefficients were calculated using SPSS 26.0, and the results are shown in Table 2. It can be seen that the quality of the system, information, service and interaction were all positively related to users' voice behavior ($\gamma_1 = 0.466$, $\gamma_2 = 0.441$, $\gamma_3 = 0.421$, $\gamma_4 = 0.385$; $p < 0.001$), and positively correlated with community identification ($\gamma_5 = 0.366$, $\gamma_6 = 0.390$, $\gamma_7 = 0.461$, $\gamma_8 = 0.356$; $p < 0.001$). Community identification was positively correlated with users' voice behavior ($\gamma_9 = 0.415$, $p < 0.001$). This preliminary finding supports the hypotheses of this study.

4.3. Confirmatory factor analysis

To avoid the common method bias, CFA proposed by Podsakoff et al. [106] was used to estimate the measurement models. As shown in Fig. 2, our proposed model (seven-factor model: system quality, information quality, service quality, interaction quality, community identification, self-disclosure, and users' voice behavior) had better fit indices ($x^2 = 1168.35$, $x^2/df = 2.64 < 3$, $p < 0.01$, CFI $= 0.95 > 0.9$, GFI $= 0.92 > 0.9$, RMSEA $= 0.05 < 0.06$) than other alternative models. For example, the three-factor model (combining system quality, information quality, service quality, interaction quality, and users' voice behavior into one factor) was used to test the distinctiveness of the mediating and moderating variables, and the fit indices were poorer ($x^2 = 5076.73$, $x^2/df = 11.01$, $p < 0.01$, CFI $= 0.65$, GFI $= 0.63$, RMSEA $= 0.12$). The results showed that the seven variables in this study had good discriminative validity, and there was no common method bias between the seven variables.

4.4. Multicollinearity test

Based on the correlation analysis presented in Table 2, all variables had correlation coefficients below 0.5. This initial finding served as the basis for a multicollinearity test. Subsequently, we employed the variance inflation factor (VIF) to assess multicollinearity among variables. The results revealed that the VIF values for system quality, information quality, service quality, interaction quality, users' voice behavior, community identification, and self-disclosure were all below 2 (VIF >10 indicates multicollinearity). There was no evidence of multicollinearity among variables.

4.5. ANOVA test

This study conducted ANOVA to explore the potential impact of different crowdsourcing virtual communities and their update frequencies on all variables. As shown in Fig. 3, the different communities (Xiaohongshu, Bilibili, Wangzhe Camp, Qingyan Camera, Jianying, CSDN, Task CN, Test Baidu, and Haier Hope) exhibited consistency in system quality, service quality, interaction quality, users' voice behavior, and self-disclosure, showing no significant differences ($p > 0.05$). However, significant differences were observed among communities in terms of information quality (F $= 2.097$, $p < 0.05$) and community identification (F $= 2.481$, $p < 0.05$).

Community update frequencies were categorized from "1 = very slow" to "5 = very fast" based on the number of updates in the past year. Thus, the update frequencies for Xiaohongshu and Jianying were rated as 5, Bilibili and Qingyan Camera as 4, Wangzhe Camp as 3, CSDN and Haier Hope as 2, and Task CN and Test Baidu as 1. As shown in Fig. 4, the different update frequencies showed consistency and no significant differences ($p > 0.05$) across service quality, interaction quality, users' voice behavior, and self-disclosure. However, update frequencies exhibited significant differences in terms of system quality (F $= 2.576$, $p < 0.05$), information quality (F $= 2.445$, $p < 0.05$), and community identification (F $= 2.532$, $p < 0.05$).

4.6. Tests of hypotheses

A hierarchical regression model was developed using SPSS to test the hypotheses, and the results are shown in Table 3. In Model 1, we controlled for the effects of demographic variables, including gender, age, education level, occupation, monthly income, and

Table 2
The results of descriptive analysis.

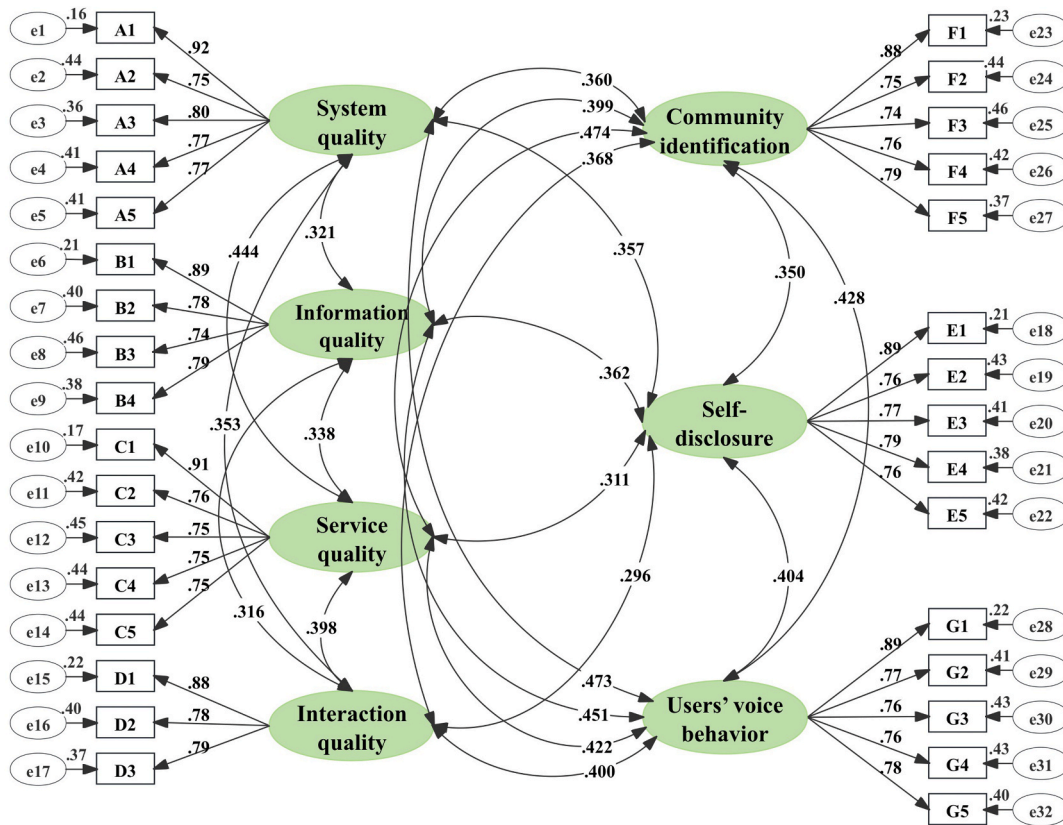| Variables	Mean	SD	1	2	3	4	5	6
1. System quality	3.123	1.001	–					
2. Information quality	3.233	0.997	0.330***	–				
3. Service quality	3.122	0.944	0.440***	0.341***	–			
4. Interaction quality	3.126	1.067	0.353***	0.304**	0.384***	–		
5. Community identification	3.232	0.954	0.366***	0.390***	0.461***	0.356***	–	
6. Self-disclosure	3.159	0.979	0.362***	0.353***	0.319***	0.291***	0.349***	–
7. Users' voice behavior	3.148	0.960	0.466***	0.441***	0.421***	0.385***	0.415***	0.396***

Note: ***$p < 0.001$.
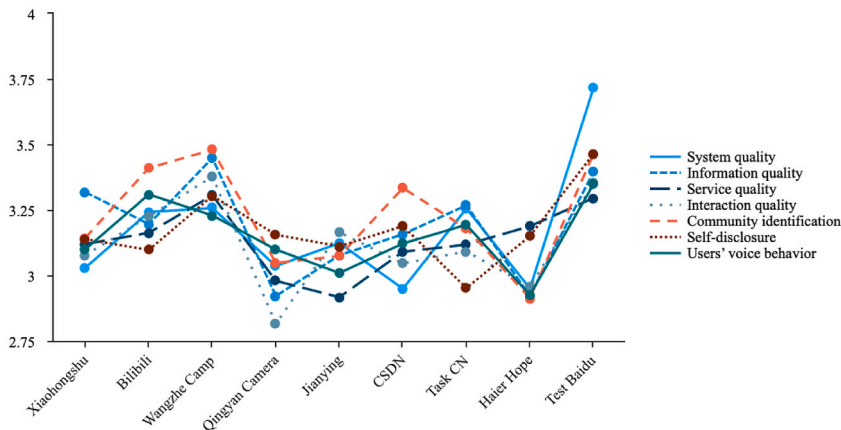
Fig. 2. The CFA of seven-factor model.

Fig. 3. ANOVA results for different crowdsourcing virtual communities.

different communities, and their update frequencies. In Model 2, after controlling these demographic variables, there were positive relationships between the quality of the system, information, service, and interaction and users' voice behavior ($\beta_1 = 0.258$, $\beta_2 = 0.249$, $\beta_3 = 0.163$, $\beta_4 = 0.159$; $p < 0.01$), respectively. Thus, Hypothesis 1 was supported. In Model 3, after controlling these demographic variables, the quality of the system, information, service, and interaction were all positively correlated to community identification ($\beta_5 = 0.120$, $\beta_6 = 0.207$, $\beta_7 = 0.278$, $\beta_8 = 0.141$; $p < 0.01$). In Model 4, after entering the demographic variables and the quality of the system, information, service, and interaction, the relationship between community identification and users' voice behavior was significant ($\beta_9 = 0.133$, $p < 0.01$).

We used the bootstrap analysis proposed by Hayes [107] to test the mediating effect of community identification. A bias-corrected 95% confidence interval (95% CI) was estimated using bootstrap samples (5000 times); the results are shown in Table 4. In Path 1, the
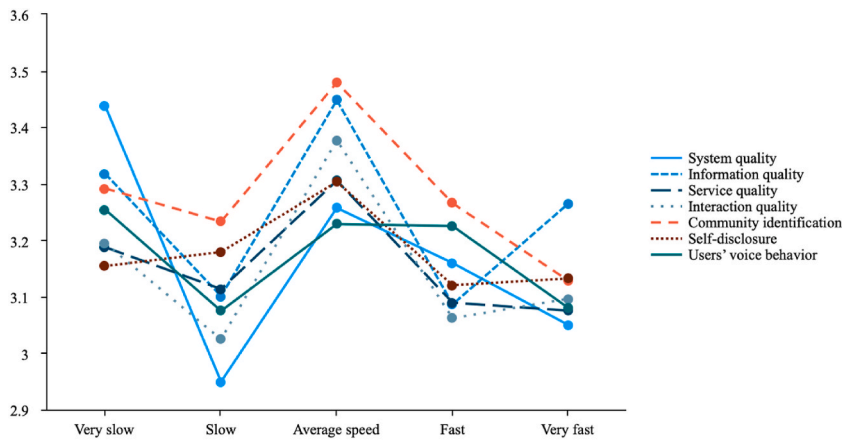
Fig. 4. ANOVA results for different community update frequencies.

Table 3
The results of hierarchical regression model.

Variables	Model 1		Model 2		Model 3		Model 4	
	Users' voice behavior		Users' voice behavior		Community identification		Users' voice behavior	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.
Gender	0.030	0.074	0.029	0.060	0.015	0.062	0.027	0.059
Age	−0.030	0.046	−0.050	0.037	−0.021	0.039	−0.047	0.037
Education level	0.016	0.035	0.010	0.028	0.020	0.029	0.007	0.028
Occupation	−0.033	0.035	−0.033	0.028	0.018	0.029	−0.035	0.028
Monthly income	−0.008	0.029	−0.028	0.024	0.031	0.024	−0.032	0.023
Different communities	−0.098	0.026	−0.022	0.021	−0.067	0.022	−0.013	0.021
Community update frequencies	−0.115	0.047	−0.025	0.038	−0.104	0.039	−0.011	0.037
System quality			0.258**	0.035	0.120**	0.036	0.242**	0.035
Information quality			0.249**	0.033	0.207**	0.034	0.221**	0.034
Service quality			0.163**	0.037	0.278**	0.038	0.126**	0.038
Interaction quality			0.159**	0.032	0.141**	0.033	0.140**	0.032
Community identification							0.133**	0.037
R^2	0.009		0.365		0.313		0.377	
$\triangle R^2$	−0.002		0.354		0.302		0.366	
F	0.818		34.467***		27.370***		33.240***	

Note: **$p < 0.01$, ***$p < 0.001$.

indirect effect of community identification between system quality and users' voice behavior was significant ($\beta_{10} = 0.015$, 95% CI = [0.004, 0.033], excluded 0). Similarity, the results of the mediating effects of information quality, service quality, and interaction quality were all significant ($\beta_{11} = 0.027$, 95% CI = [0.011, 0.048]; $\beta_{12} = 0.038$, 95% CI = [0.015, 0.063]; $\beta_{13} = 0.017$, 95% CI = [0.006, 0.036]), and the 95% CI for each pathway excluded 0. Thus, Hypothesis 2 was supported.

The moderating effect was tested using three models. Model 5 included the control variables and community identification. Model 6 added a moderating variable (self-disclosure) based on Model 5, and Model 7 added interaction terms (community identification × self-disclosure) based on Model 6. Table 5 presents the results. In Model 7, the interaction term between community identification and self-disclosure was significantly related to users' voice behavior ($\beta_{14} = 0.204$, $p < 0.01$). Thus, Hypothesis 3 was supported. As per Aiken and West's study [108], a Simple slope test was used to analyze the moderating effect of self-disclosure at different levels (Mean ± 1SD); the results are shown in Fig. 5. The higher the self-disclosure, the stronger the positive influence of community identification on users' behavior (Simple slope β = 0.511, $p < 0.001$); the lower the self-disclosure, the lower the positive effect of community

Table 4
The results of the mediating effect test.

Mediating path	Total effect	Direct effect	Indirect effect	Boot SE	95% CI
Path 1: System quality → Community identification → Users' voice behavior	0.248**	0.232**	0.015	0.008	[0.004, 0.033]
Path 2: Information quality → Community identification → Users' voice behavior	0.239**	0.213**	0.027	0.010	[0.011, 0.048]
Path 3: Service quality → Community identification → Users' voice behavior	0.165**	0.128**	0.038	0.012	[0.015, 0.063]
Path 4: Interaction quality → Community identification → Users' voice behavior	0.143**	0.126**	0.017	0.008	[0.006, 0.036]

Note: **$p < 0.01$.

Table 5
The results of the moderating effect test.

Variables	Model 5		Model 6		Model 7	
	Users' voice behavior		Users' voice behavior		Users' voice behavior	
	β	S.E.	β	S.E.	β	S.E.
Gender	0.024	0.068	0.010	0.065	0.023	0.063
Age	−0.028	0.042	−0.023	0.040	−0.028	0.039
Education level	0.007	0.032	0.001	0.030	0.005	0.029
Occupation	−0.042	0.032	−0.029	0.030	−0.036	0.030
Monthly income	−0.026	0.027	−0.035	0.026	−0.039	0.025
Different communities	−0.036	0.024	−0.048	0.023	−0.047	0.023
Community update frequencies	−0.035	0.043	−0.044	0.041	−0.050	0.040
Community identification	0.414**	0.036	0.315**	0.037	0.291**	0.036
Self-disclosure			0.285**	0.035	0.274**	0.035
Community identification × Self-disclosure					0.204**	0.036
R^2	0.177		0.248		0.288	
$\triangle R^2$	0.177		0.071		0.040	
F	17.819***		24.210***		26.754***	

Note: **$p < 0.01$, ***$p < 0.001$.

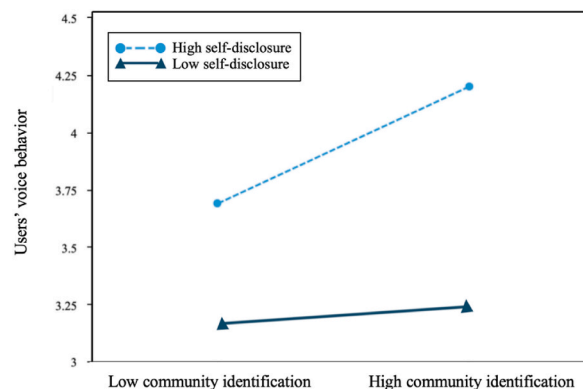identification on users' voice behavior (Simple slope $β = 0.074$, $p < 0.001$).

5. Discussion

This study investigated how the quality of a crowdsourcing virtual community affects users' voice behavior. Drawing on the SOR model and Social Identification Theory, this study revealed that the quality of a crowdsourcing virtual community includes system, information, service, and interaction qualities. This can enhance the users' voice behavior through the mediating role of community identification. Moreover, self-disclosure moderates the relationship between community identification and voice behavior. The theoretical and practical implications of this study are discussed below.

5.1. Theoretical implications

First, scholars have realized that users, as the main sources of suggestions and creativity in crowdsourcing virtual communities, play an important role in promoting community development. However, a literature review reveals that research on user behavior within crowdsourcing virtual community platforms tends to focus more on users' knowledge sharing behavior, engagement, and innovation [2,22,24,25,57,64,67,69,70], with relatively less attention paid to users' voice behavior. There is also limited research on how the quality of crowdsourcing virtual communities affects users' emotions, cognition, and behavior. Therefore, this study addresses these gaps by introducing a focused examination of users' voice behavior within crowdsourcing virtual communities. Our emphasis is on delving into the factors that influence user expression through language, comments, and feedback within the community. A distinctive theoretical implication of our research lies in its in-depth definition and analysis of the quality of crowdsourcing virtual communities. We propose a multidimensional structure, including system, information, service, and interaction quality, asserting their significant roles in promoting users' voice behavior. This contribution not only refines the conceptualization of crowdsourcing virtual community quality but also expands the antecedents of users' voice behavior.

Second, based on the SOR model and Social Identification Theory, this study investigates the influence mechanism between the

Fig. 5. The moderating effect of self-disclosure on the relationship between community identification and users' voice behavior.

quality of the crowdsourcing virtual community and users' voice behavior, namely the mediating role of community identification. Most previous research was mainly based on Self-presentation Theory, Technology Acceptance Model, Social Capital Theory, and so on [109–112], and examined the effects of the quality of the crowdsourcing virtual community on users' trust, satisfaction, community engagement, and community climate [13,18,21,83,87]. However, in this study, the SOR model and Social Identification Theory explain that the quality of the crowdsourcing virtual community is a key factor in users' perceptions of the system, information, service, and interaction characteristics of the community, inducing the psychological emotion of community identification, which affects users' voice behavior. Therefore, this contributes to the refinement and extension of the SOR model. Moreover, by developing a "crowdsourcing virtual community quality (S)–community identification (O)–users' voice behavior (R)" model, our study enriches the understanding of how these elements interrelate specifically in the context of crowdsourcing virtual communities. This finding not only confirms the significance of community identification but also emphasizes its role as a mediating mechanism that influences users' voice behavior in such communities.

Third, this study introduced self-disclosure as a moderating variable and confirmed that individuals with stronger self-disclosure tendencies are more likely to convert their psychological emotions into individual expressions and community identification. Consequently, they exhibit a greater propensity to engage in voice behavior. This finding suggests that the extent to which users disclose themselves influences how their community identification translates into voice behavior. This is a new theoretical perspective for exploring the boundary conditions of the impact of virtual community quality on user behavior. This sheds light on the intricate interplay between personal characteristics and participation within a crowdsourcing virtual community, expanding existing studies on user behavior within these virtual platforms.

5.2. Practical implications

From a managerial perspective, leveraging the SOR framework in the context of crowdsourcing virtual communities and focusing on community quality (comprising system, information, interaction, and service quality) is crucial. For example, enhancing system quality to optimize user participation and feedback requires constant evaluation and refinement by managers. Emphasizing information quality ensures accurate, reliable, and updated content. Interaction quality should prioritize intuitive interfaces, user-friendly designs, and active community engagement. Service quality requires responsive customer support and timely issue resolution. These measures collectively foster a sense of community identification among users, thereby stimulating positive users' voice behavior. Moreover, recognizing the role of self-disclosure in users' voice behavior enables managers to encourage individual expression without compromising user comfort or privacy, ultimately facilitating and sustaining a conducive environment for constructive user feedback.

From the user's perspective, recommendations tailored to enhance the experience of crowdsourcing virtual communities are crucial. First, users should actively engage in high-quality content and discussions, and provide constructive feedback. Seeking and sharing accurate and valuable information ensures the quality of a community's information. Participating in community activities, responding to queries, and helping others improve interaction quality. In addition, utilizing and providing feedback on available support services boosts service quality. Furthermore, users should recognize the role of self-disclosure in influencing community identification and feedback behaviors. Balancing self-expression while respecting personal comfort levels is essential to ensure a supportive and secure environment for fruitful interactions within the virtual community.

5.3. Limitations

Although the results of this study contribute to theoretical research and management practices, there are certain limitations that future studies can address for further improvement. First, this study adopted a questionnaire survey to collect data, and there may have been some measurement errors associated with cross-sectional data. Despite employing various methods during the questionnaire collection process to minimize measurement errors, such as providing detailed explanations and guidance to ensure participants' comprehension of the questions, and methods such as CFA and multicollinearity test to ensure data accuracy, the cross-sectional nature of the data can only offer momentary insights at specific time points. This limitation means that our study may not fully capture the dynamic changes in community quality and user behavior over time. To establish a more robust understanding of the logical relationships between the variables, future research could employ a longitudinal research design with time intervals to provide more comprehensive evidence for hypotheses testing. By adopting a longitudinal approach, researchers can strengthen the robustness of their findings and contribute to the theoretical foundation of the field.

Second, based on SOR framework, this study explored the mediating role of community identification in the relationship between community quality and users' voice behavior. However, this study did not consider whether other emotional experiences triggered by the external stimulus of the quality of crowdsourcing virtual communities could also function as a mediating variable. Future research should explore the potential mediating effects of various emotional experiences elicited by the quality of crowdsourcing virtual communities on users' voice behavior. This would provide a more comprehensive understanding of the emotional dynamics that influence users' voice behavior in virtual community settings.

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Data available statement

The datasets used and analyzed in this study are available from the first author on reasonable request.

Ethics declarations

This study was reviewed and approved by Ethics Committee of School of Economics and Management, Beijing Information Science and Technology University, with the approval number EA202301018. All participants provided informed consent to participate in the study.

CRediT authorship contribution statement

Ganli Liao: Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Conceptualization. **Jing Wang:** Writing – original draft, Resources, Methodology, Data curation. **Qichao Zhang:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Xin Ding:** Resources, Methodology, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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