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Understanding Sustained Knowledge Contribution from a Motivation Crowding Perspective: A Case Study in a Chinese Q&A Community

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Abstract: A Q&A community typically employs various types of external incentives to motivate knowledge contribution from their community members. This study aims to examine the effects of different external incentives, which are conceptualized as different types of motivational factors, on community participants' sustained knowledge contribution. Drawing on motivation crowding theory, the present study proposes that different motivators interact and jointly influence knowledge contribution behavior. The panel data were collected from a Chinese Q&A community by using the Python Scrapy crawler, and the Poisson regression model with fixed effects was used to validate the integrative model. The results revealed that generalized reciprocity and social learning undermined the effect of online attractiveness on sustained knowledge contribution, whereas peer feedback strengthens this effect. The findings contribute to the extant research on sustained contribution behavior and provide practical insights into sustaining virtual communities.

Keywords: sustained knowledge contribution; motivation crowding theory; Q&A virtual community; intrinsic motivation; extrinsic motivation

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1. Introduction

Conceivably, a Q&A community cannot last long without the sustained contribution of its members [1,2]. A thriving Q&A community features great involvement and participation of its members, who not only obtain knowledge contributed by others but also contribute their own knowledge [3]. How to encourage community participants to sustainably contribute has been a key concern that has attracted significant attention from researchers and practitioners.

The literature has documented different reasons why participants sustainably contribute knowledge to their community. Generally speaking, some of those reasons relate to participants' intrinsic motivations: they contribute because they enjoy helping others or they have psychological needs to attain a good reputation and/or a desire for gaining online attractiveness [4]. Other reasons involve different external motivational factors, such as reciprocity [5,6] and peer feedback [7,8]. While extant research has tested the effects of various types of motivation on contribution, they have also presented conflicting findings in terms of these effects. For instance, Zhao et al. [4] demonstrated that the motivator of reciprocity weakens the impact of self-efficacy on the intention to contribute, while Zhang et al. [9] found the opposite, i.e., that reciprocity strengthens such an effect. Furthermore, Zhao et al. [4] suggested that rewards weaken the effect of enjoying helping others through contribution, while Andersen et al. [10] argued that it strengthens this effect.

Driven by these inconsistent findings, this study aims to explore the potential nuanced interaction effects that arise from both the intrinsic and extrinsic motivations on sustained knowledge contribution. According to previous studies [4,6,11,12] and relevant to our focal context, we conceptualize the extrinsic motivational factors as manifested by reciprocity, social learning and peer feedback, and intrinsic motivation as reflected by gaining online attractiveness. Drawing on motivation crowding theory [13,14], we theorize why and how different manifestations of extrinsic motivation interplay with intrinsic motivation to influence participants' contribution behavior. Using a Poisson regression model with fixed effects, our findings contribute to both the community contribution literature and motivation crowding theory. Particularly, in line with and extending the current literature [4,15], our findings, to some extent, explain the past inconsistent findings. Moreover, we provided a more nuanced examination to show how different manifestations of extrinsic motivation moderate the impact of intrinsic motivation on contribution behavior. To this end, we empirically extend motivation crowding theory.

The rest of the paper is organized as follows: the next section, Section 2, reviews the literature on motivations for sustained knowledge contribution in a virtual community and motivation crowding theory. Section 3 develops our research model and hypotheses. Section 4 introduces the research methodology, which includes the model estimation and research results. Last, Section 5 discusses our findings and implications for research and practices.

2. Literature Review

2.1. Motivations for Sustained Knowledge Contribution

The most asset of a virtual community is the sustained knowledge contribution from the community participants. This has driven great academic efforts to examine sustained contributions in virtual communities. Basically, the extant literature concludes that different types of motivation can lead participants to contribute [6,7,11,16]. For instance, Dong et al. [3] and Jin et al. [11] suggested that extrinsic motivations—social learning and peer recognition—positively influence people's sustained knowledge contribution. Sun et al. [16] found that extrinsic and intrinsic motivations both positively relate to sustained knowledge contribution, but implied that their interaction effect might be complex. Building upon the conceptualization of previous research [17], our study investigates three types of extrinsic motivation—normative motivation, social motivation, and symbolic motivation. Specifically, we examine how these extrinsic motivations interact with intrinsic motivation—manifested as the hedonic motivation, to influence sustained knowledge contribution. Table 1 summarizes the different types of contribution motivations discussed in this study.

Table 1. Summary of virtual community contribution motivations.

Motivation	Manifested as	References
Normative motivation	Generalized reciprocity	[6,18]
Social motivation	Social learning	[11,19]
Symbolic motivation	Peer feedback	[6,7]
Hedonic motivation	Online attractiveness	[5,12]

Normative Motivation. Prior research suggested that an individual's contribution is largely driven by community norms [20,21] because norms implicitly establish agreement among members regarding when and how to engage in group activities [22]. Norms are widely shared beliefs regarding how group members should behave, and they push one to adjust behavior to conform to community norms. A commonly upheld community norm is generalized reciprocity [6,15], which obligates participants to give back to the community by contributing their own knowledge. Reciprocity involves the general community members, and the exchange of knowledge, to some extent, reflects the ultimate value of fairness [23,24].

Social Motivation. Social motivation refers to people's desire to maintain a learning relationship with others [17]. As a typical type of social motivation, social learning occurs because of observing the behavior of others and the outcomes of that behavior [11,24]. An individual can form and maintain a learning relationship with others through social learning. This learning relationship can help improve one's own knowledge and promote long-term knowledge exchange.

Symbolic Motivation. Symbolic motivation indicates that individuals may take on certain actions for symbolic reward. Peer feedback is deemed an important exemplar of symbolic reward [7]. Peer feedback refers to perceived support (e.g., encouragement or positive feedback) from a community or individual members [6,7,25]. It is not only an acknowledgment of the value of one's contribution but also an incentive for future contribution [6,26]. For example, in a Q&A community, knowledge contributors may get recognized by other members, who "vote" for or "like" their contribution.

Hedonic Motivation. In contrast to normative, social, and symbolic motivations, which are different types of extrinsic motivational mechanisms, hedonic motivation reflects an intrinsic motivation [17]. Hedonic motivation stems from the intrinsic reward to engage in an activity. That is, the behavior of contribution itself can reward participants with feelings of inherent satisfaction because contribution could help one to gain attractiveness, a good reputation, and enjoyment [17,27,28]. In a Q&A community, a knowledge contributor can obtain intrinsic rewards as his or her audience increases [29], because a large size of audience indicates a high level of online attractiveness. Online attractiveness reflects how popular the contributor is in a community, and is directly related to how rewarding the contribution behavior is to the contributor [5].

Although it is well documented that different types of motivation play a significant role in influencing participants' sustained knowledge contribution in Q&A virtual communities, relatively little research has studied how different motivations interplay with each other. To better understand this issue, we draw on motivation crowding theory [14].

2.2. Motivation Crowding Theory

Motivation crowding theory (henceforth MCT) [4,14] posits that intrinsic and extrinsic motivations coexist in driving individuals' decision-making. Intrinsic motivation is geared toward internal rewards and reinforcers, such as enjoyment, achievement, and a sense of competence, while extrinsic motivation is geared toward external rewards and reinforcers, including monetary incentives, some forms of praise, or policies. MCT states that the two types of motivation interact and jointly affect behavior through the crowding-out and crowding-in effects. Motivation crowding out refers to the effect that extrinsic motivators (e.g., payment) can undermine intrinsic motivation, while the *crowding-in* effect suggests that extrinsic motivators may strengthen the effect of intrinsic motivation [30]. Whether external motivators crowd out or crowd in intrinsic motivation depends on individuals' perception of the external motivators [14]. Take monetary incentives as an example, if a monetary incentive is perceived as a means to control people's self-determination and thus infringes on their autonomy, the incentive reduces, or crowds out, their intrinsic motivation to engage in the focal activity [31]. If the monetary incentive is seen as a supportive resource, it will become a positive factor that boosts, or crowds in, intrinsic motivation [30].

MCT has been acknowledged by economists and social psychologists as a highly useful explanatory framework for understanding people's behavioral performance. The theory has been extensively tested in many behavior domains, such as public service [32], online product reviewing [33], and prosocial behavior [34]. For instance, Zhao et al. [4] argued that monetary incentives and reciprocity weaken the influence of willingness to help and self-efficacy on contribution attitude. Zhang et al. [9] suggested that material incentives undermine the influence of intrinsic motivation on contribution behavior. Hausberg and Spaeth [19] argued that reputation undermines the influence of intrinsic motivation on contribution. Andersen et al. [10] demonstrated that external reward strengthens the effect of enjoying helping others. Although MCT has been recognized as a valuable framework to explain the interplay between extrinsic and intrinsic motivations, it has not been applied to test the intricacies across different types of extrinsic motivation, nor has it been tested in online contexts such as virtual communities. Inspired by previous studies such as [6,12,18,19], we examine three types of extrinsic motivation that embody different underlying mechanisms, namely, normative motivation, social motivation, and symbolic motivation. To this end, we potentially contribute to MCT.

In addition, studying different forms of extrinsic motivations in virtual communities is important because, in virtual communities, participants devote time and effort to contribute knowledge voluntarily without receiving essential monetary compensation [35–37]. Thus, to motivate members to contribute, the design of other types of incentive mechanisms deserves more attention. However, little research has analyzed the potential interaction effects among various types of motivations in promoting sustained knowledge contribution through the motivation crowding perspective. Moreover, as the member participates in the community over time, members' participation motivation, values, and attitudes may change [22]. For example, Xia et al. [38] suggested that the intensity of initial motivations may change over time. Sun et al. [16] argued that initial motivation factors for contribution might not be sufficient to account for sustained contribution. Zhang et al. [39] suggested that the antecedents of initial contribution behavior may differ from those of sustained contribution since the factors may change based on subsequent behaviors. It is thus important to investigate the nuanced impacts of various types of motivational mechanisms on sustained contribution over time.

3. Research Model and Hypotheses

The present study tests the moderating effects that extrinsic motivations moderate the impact of intrinsic motivation on sustained contributions (i.e., H1a, H2a, H3a). Our research model can be found in Figure 1, which summarizes the relationship paths we seek to test.

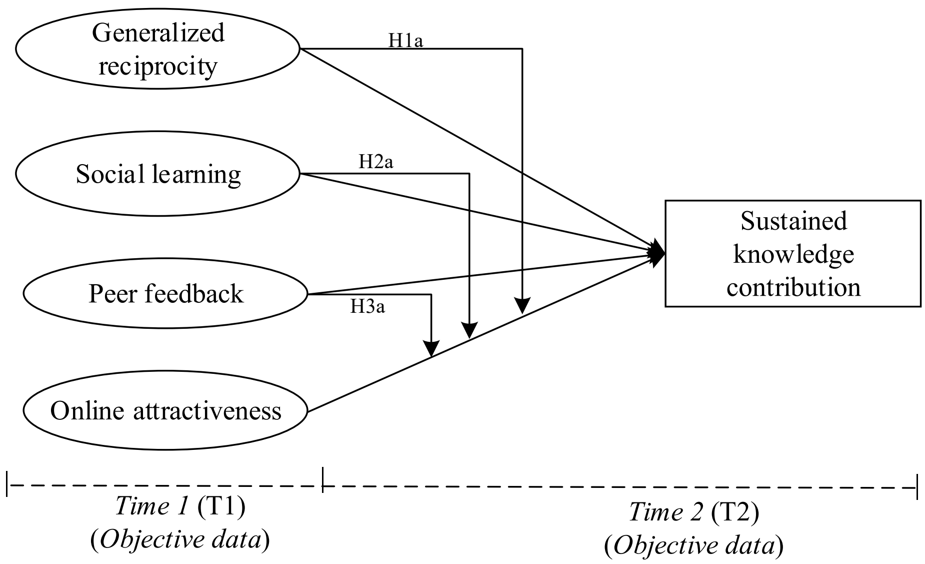

Figure 1. Research model.

Members can be motivated to answer others' questions for hedonic reasons, such as to attract more attention [12]. However, members may perceive that those who contribute only do so to comply with community norms of reciprocity [4]. Influenced by these perceptions, participants are likely to perceive themselves to be controlled by generalized reciprocity; this perception may negatively influence the motivational effect of online attractiveness. In other words, participants may be inclined to attribute the contributions to as a practice to comply with community norms of reciprocity, rather than to perceive that their contribution behavior is motivated by online attractiveness. Therefore, we hypothesize:

Hypothesis 1a. *Generalized reciprocity undermines the impact of online attractiveness on sustained knowledge contribution.*

Online attractiveness is typically obtained by contributing good knowledge to the community, and it reflects one's popularity and knowledge independence [12]. Participants who have a high level of online attractiveness might tend to exert influence on the viewpoints and decisions of others, rather than being influenced by others. That is, they are less likely to learn from or follow other members [38,40]. However, the purpose of social learning is to improve one's knowledge and ability, which means that they need to be in a "receiving" mode [40]. Thus, it is not surprising that the members in the receiving mode get intimidated and perceive their knowledge independence and capability to be challenged. In line with the crowding-out effect, social learning crowds out the influence of online attractiveness [14]. Therefore, we predict:

Hypothesis 2a. *Social learning undermines the impact of online attractiveness on sustained knowledge contribution.*

Online attractiveness is predicted to positively impact contribution behavior, but the impact may be undermined by gaining peer feedback. Specifically, once peer feedback is introduced as a symbolic motivation for knowledge contribution, members may lose interest in improving online attractiveness. Since peer feedback conveys symbolic meanings related to acknowledgment and positive recognition, it can not only satisfy the user's need for competence [7] but also verify their attractiveness and popularity in the community [11]. Thus, gaining peer feedback may weaken the motivation to achieve online attractiveness. Therefore, the following hypothesis is proposed:

Hypothesis 3a. *Peer feedback undermines the impact of online attractiveness on sustained knowledge contribution.*

4. Research Methodology

4.1. Research Context and Research Data

Zhihu, a Chinese equivalent of Quora, served as the research context of this study. On this platform, members can post questions, provide answers, and exchange knowledge [41]. The community provides publicly visible member profiles, question logs, answer data, and social dates on the personal homepage. We initially collected 3000 users over eight months from February to September 2018 using the Python Scrapy crawler. To better characterize the behavior of sustained knowledge contribution, only active members are chosen for analysis. Guided by prior research, the monthly data cover a sufficiently long period and are suitable for analyzing members' sustained contribution behavior in online settings [6,11,38].

To observe the dynamic changes in knowledge contribution behaviors, we only capture the periods prior to changes in behavior. Figure 2 illustrates the definition of our data points. A "0" indicates that the member did not post an answer during the period. A "1" indicates that the member posted at least one answer during the period. The circle in Figure 2 is a data point that corresponds to a month after the one in which the member contributes [38]. Consistent with prior research such as Jin et al. [11] and Guan et al. [6], we select members who exhibit knowledge contribution behaviors in at least two periods. Out of all members, 1467 were considered members who make sustained knowledge contributions.

		Month 1	Month 2	Month 3	Month 4	Month 5	......
Member 1	0	1	1	1	0	0	......
Member 2	0	0	0	1	0	0	......
Member 3	0	1	0	1	1	0	......
Member 4	0	0	1	1	0	0	......
Member 5	0	1	0	0	1	0	......
......	......	......	......	......	......	......	......

Figure 2. Data point illustration.

4.2. Variable Measurement and Descriptive Statistics

Sustained knowledge contribution. Sustained knowledge contribution is the dependent variable of this study, according to prior research [3,11], which was measured by the number of newly contributed answers by a member per month.

Generalized reciprocity. On Zhihu, reciprocity is the basis of social exchange [23]. When members want to get more answers to their own questions, they would contribute more knowledge to the community. In this study, generalized reciprocity was measured as the number of answers received by a member per month.

Peer feedback. On Zhihu, one of the most important ways for members to show their approval for others' answers is by giving a "like"; a "like" indicates that "an answer is worth reading". In line with the conceptualization of "peer feedback", we used the number of likes gained by each member per month to measure the amount of peer feedback.

Online attractiveness. On Zhihu, the most intuitive and effective communication channel is members' followers, which represents the online attractiveness of a member. To better clarify online attractiveness, we need to find a variable that can reflect their continuous attractiveness process. In light of Toubia and Stephen [29], we used the number of new followers by each member per month to measure online attractiveness.

In accordance with the research hypotheses of this paper, there may be potential endogeneity issues resulting from reverse causality, i.e., the temporal and logical connection between these independent variables and dependent variables [7]. As shown in the model specification, we lagged the value of independent variables by one month to reduce the potential endogenous problem. Table 2 defines all variables and shows the results of variable descriptive statistics.

Table 2. Descriptive statistics.

Construct	Measure Item	Mean	Std. Dev.	Min	Max	Reference
Sustained Knowledge Contribution	SKC_{it}	5.471	9.774	0	63	[3,6]
Generalized Reciprocity	GR_{it}	0.143	0.796	0	51	[5,18]
Social Learning	SL_{it}	4.667	8.699	0	56	[11,41]
Peer Feedback	PF_{it}	4168.515	7939.327	13	48,913	[6,18]
Online Attractiveness	OA_{it}	1730.374	4208.864	2	28,881	[12,29]

As shown in Table 3, the dependent variable had positive correlations with the independent variables; the variance inflation factor (VIF) of the independent variables ranged from 1.04 to 1.19. Thus, multicollinearity was not considered a severe problem [42].

Table 3. Correlation matrix.

Variable	V0	V1	V2	V3	V4	VIF
V 0 SKC_{it}	1.00					
V 1 GR_{it}	0.16	1.00				1.04
V 2 SL_{it}	0.26	0.18	1.00			1.09
V 3 PF_{it}	0.49	0.10	0.21	1.00		1.19
V 4 OA_{it}	0.18	0.09	0.12	0.37	1.00	1.14
			Mean VIF			1.12

We controlled some factors that could influence sustained knowledge contribution, such as culture-level and individual-level characteristics (education, culture and face concern, etc.) that we were unable to observe [7,43]. Therefore, we included individual-fixed effects to explain all unobserved heterogeneity. Similarly, to control for these time-dependent factors that are not reflected in the aggregate network measurement, we introduced time-fixed effects [38]. The panel data included both cross-section data and time-series data, which were prone to the phenomenon of "pseudo-regression". To avoid pseudo-regression and ascertain the availability of estimation results, a panel unit root test should be implemented on every variable. Based on different data generation processes, a variety of unit root test methods have been proposed for analyzing panel data, such as the LLC [44], IPS [45], Fisher-ADF [46], and PP [47] tests. To ensure the robustness of our results, these methods were used to conduct a unit root test. As shown in Table 4, all variables were significant at the 1% significance level, which met the basic requirements for establishing the model.

Table 4. Stationarity test.

		Dependent Variable	Independent Variable			
		SKC	**GR**	**SL**	**PF**	**OA**
LLC	Statistic	−68.7709	−21.8738	−264.185	−169.404	−92.7061
	Prob.	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
IPS	Statistic	−20.4126	−5.87514	−25.2725	−22.7173	−6.84768
	Prob.	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fisher-ADF	Statistic	5034.27	640.143	4258.51	5034.81	3898.48
	Prob.	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PP	Statistic	6392.47	788.052	5137.70	6106.36	4521.54
	Prob.	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

In addition, this study used the Kao test for co-integration analysis. According to the results of the Kao residual co-integration test (as shown in Table 5), the variable passed the co-integration test and thus could be applied to regression analysis.

Table 5. Co-integration test.

Test Method	Statistic Name	t-Statistic	Prob.
Kao Residual Co-integration Test	ADF	−8.1316	0.0000

4.3. Model Specification and Estimation

The dependent variable, in this article, was the number of answers posted by each member per month. Because it was a count variable, both Poisson (henceforth PO) regression and negative binomial (henceforth NB) regression were the appropriate models to deal with such dependent variables [8]. The model is as follows:

$$Pr(Y = y_{it}/X_{it}) = \frac{\Gamma(y_{it}+\theta)}{\Gamma(y_{it}+1)\Gamma(\theta)}\left(\frac{\theta}{\theta+exp(X_{it}\beta)}\right)^{\theta}\left(\frac{exp(X_{it}\beta)}{\theta+exp(X_{it}\beta)}\right)^{y_{it}} \quad (1)$$

where i is indexed observational units and t is indexed time, $y_{it}= \{0,1,2,3\ldots\}$ was the dependent variable, X_{it} was a vector of covariates for member i at time t, β was a vector of regression coefficients of covariates, and $\lambda = exp(X_{it}\beta)$ was the expected value of the distribution. When $\theta = 0$, NB was the same as the Poisson regression.

In addition, for the panel models, we need to select between fixed effects (henceforth FE) and random effects (henceforth RE). The difference between these two models is that the RE assumes that observed covariates are independent of the individual effects, while the FE relies on the variance within individuals and reduces the misgiving of individual effects, which ensures consistent estimates [48]. We performed the Hausman test on the NB regression model (χ^2 = 135.68, p < 0.001) and the PO regression model (χ^2 = 141.43, p < 0.001) separately. According to the results of Hausman's [49] test, we conjected that the FE model was more suitable for our research. However, when using the NB regression model with FE to analyze short panel data, an "incidental parameters problem" usually occurs [48]. Accordingly, we did not consider the NB model as its unconditional FE estimator results in inconsistent estimates [7], while its conditional FE estimator was not a "true fixed effects" model and could lead to biased estimates unless in very restrictive conditions [7]. Thus, we used the Poisson regression (henceforth PO) with FE to investigate our research question.

Due to the existence of interaction terms, we employed the hierarchical regression model to investigate the main effect and moderating effects, respectively [3]. To reduce possible multicollinearity problems, all independent variables had been mean-centered before the interaction terms were established [41]. The regression model is:

$$\begin{aligned}\lambda(SKC_{it}) &= c_i + \sum_{k=1}^{K} X_{it-1}\beta_k + \varepsilon_{it} \\ &= c_i + \beta_1 \times GR_{it-1} + \beta_2 \times SL_{it-1} + \beta_3 \times PF_{it-1} + \beta_4 \times OA_{it-1} + \beta_5 \times GR_{it-1} \times OA_{it-1} \\ &\quad + \beta_6 \times SL_{it-1} \times OA_{it-1} + \beta_7 \times PF_{it-1} \times OA_{it-1} + \varepsilon_{it}\end{aligned} \quad (2)$$

4.4. Results

Table 6 and Figure 3 showed the estimated results of the panel PO regression model with FE. Models 1–3 explained the moderating effects by sequentially adding interaction items step by step to offer a much clearer identification and interpretation. The significance of regression coefficients of all variables did not change, indicating that these models had good stability. The interpretation of all hypotheses in this paper was mainly based on Model 3, which contained all independent variables and interaction terms.

H1a, H2a, and H3a investigated the moderating effects of generalized reciprocity, social learning, and peer feedback on the link between online attractiveness and sustained contribution, respectively. The regression results showed that generalized reciprocity and social learning undermined the impact of online attractiveness on sustained knowledge contribution. Thus, hypotheses 1a ($\beta = -0.00702, p < 0.01$) and 2a ($\beta = -0.110, p < 0.01$) were supported. For H3a, peer feedback strengthened the impact of online attractiveness on sustained contribution ($\beta = 0.0100, p < 0.05$). Therefore, hypothesis 3a was not supported.

Table 6. Regression results.

	M1	M2	M3
GR_{it}	0.0511 *** (0.0122)	0.0515 *** (0.0120)	0.0524 *** (0.0118)
SL_{it}	0.106 *** (0.0152)	0.116 *** (0.0153)	0.116 *** (0.0153)
PF_{it}	0.465 *** (0.0496)	0.475 *** (0.0495)	0.469 *** (0.0496)
OA_{it}	0.372 ** (0.183)	0.370 ** (0.184)	0.362 ** (0.184)
$GE_{it} \times OA_{it}$	−0.00612 *** (0.00176)	−0.00617 *** (0.00173)	−0.00702 *** (0.00175)
$SL_{it} \times OA_{it}$		−0.0938 *** (0.0351)	−0.110 *** (0.0357)
$PF_{it} \times OA_{it}$			0.0100 ** (0.00402)
AIC	39,723.79	39,678.66	39,647.08
BIC	39803.38	39,765.49	39,741.15
Specification	FE	FE	FE
Time-Fixed Effects	Included	Included	Included
User-Fixed Effects	Included	Included	Included
Log Likelihood	−19,850.894	−19,827.331	−19,810.541
Wald Chi2	909.43 ***	1044.57 ***	959.85 ***

*** $p < 0.01$, ** $p < 0.05$.

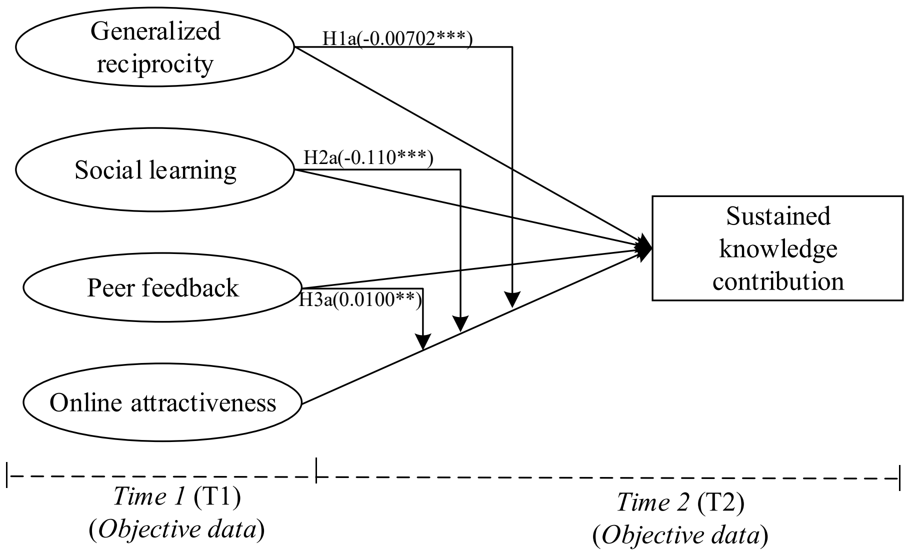

Figure 3. The revised research model. *** $p < 0.01$, ** $p < 0.05$.

5. Discussions and Conclusions

5.1. Findings

Building upon motivation crowding theory, this study examined the main effects of extrinsic motivations (i.e., generalized reciprocity, peer feedback, and social learning) and intrinsic motivation (i.e., online attractiveness) on sustained knowledge contribution and the related moderation effects. Using data from a large online Q&A community, we found that generalized reciprocity, peer feedback, social learning, and online attractiveness positively influence sustained knowledge contribution. With respect to the moderation effect, in line with the theorization, we showed that both the generalized reciprocity and social learning negatively moderate the effects of online attractiveness on sustained knowledge contribution. However, interestingly, peer feedback positively moderates the effect of online attractiveness on sustained knowledge contribution.

One possible reason is that when people accumulate a certain number of followers, they would like to hear the voices of followers to validate their attractiveness. Peer feedback conveys a wide range of symbolic messages that satisfy users' need for competence [7] and verify members' attractiveness in the community [11]. In this process, peer feedback may reinforce online attractiveness, so that the possibility of its transformation into actual behavior increases. Another possible reason is that if members only attain others' attention, but fail to gain any feedback, it would be impossible to affirm their own attractiveness and popularity by the general public [29]. Thus, the effect of attractiveness on knowledge contribution will be greatly discounted. In other words, peer feedback can strengthen online attractiveness if members perceive such feedback as supportive. Under the circumstances, self-determination and self-esteem will gradually develop, and members may realize that they have more incentives to act, thus enlarging their contribution.

5.2. Theoretical and Practical Implications

This study offers important contributions. First, this paper extends the existing research on knowledge contribution in Q&A virtual communities. How to design effective mechanisms to motivate community participants to contribute knowledge is always the key question researchers and practitioners are concerned with [24,36]. In the past decade, a growing body of research has identified the extrinsic design factors that may influence intrinsic motivation but failed to reach an agreement [4,9]. One possible reason is that they did not distinguish the differences between initial knowledge contribution and sustained knowledge contribution [4,38]. The present study provides an additional piece of work to explain the potential interaction effects between the intrinsic and extrinsic motivations, which jointly influence sustained knowledge contribution.

Second, this study extends the current understanding regarding MCT by examining the effects of various types of extrinsic motivation. Specifically, MCT has clearly explained the effects regarding how extrinsic motivation undermines or strengthens the intrinsic in affecting behavior performance, it is scantly studied regarding different effects introduced by different types of extrinsic motivation on the intrinsic motivation, thus leading to rich interesting findings [6,12,18,19]. This study meticulously analyzes different types of extrinsic motivation that are tightly related to design mechanisms in Q&A virtual communities. It reveals that some of the extrinsic motivation factors positively moderate intrinsic motivation, while some of them would bring negative moderation effects, thus extending the understanding of this theory in the focal context.

The findings of this study also provide guidelines for practitioners. When community managers motivate members to contribute knowledge, they should be aware of various types of motivation that are not additive in nature [4,30]. That is, either the crowd-out or crowd-in effect would happen. Our findings suggest that generalized reciprocity and social learning undermine the effect of online attractiveness on sustained knowledge contribution. Specifically, generalized reciprocity creates a moral constraint (e.g., a sense of indebtedness), while social learning may expose one's incapability. Both of these motivations can be regarded as a restriction factor for individuals to demonstrate online attractiveness. Constrained by these perceptions, participants may realize that their online attractiveness will not be appreciated or they must comply with the community norm. Consequently, when members have already been motivated by intrinsic motivation, community operators should be cautious when introducing normative motivation due to the negative influence on intrinsic motivation, that is, community operators should be aware of the crowding-out effect.

Although prior research argues that there may be a "mutual contradiction" among multiple motivations [4,15], the results show that this is not always the case. For example, symbolic motivation can strengthen the influence of intrinsic motivation on sustained knowledge contribution. At present, symbolic motivations are widely used in practice, such as upvotes, accepted answers, and badges. It is essential for community operators to realize applying peer feedback to represent one's competence can not only strengthen the effect of intrinsic motivation but also increase the possibility of promoting actual behavior. For design, community operators should reduce the feedback cost of knowledge readers, such as by setting the “like” button in a prominent place. Similarly, a symbolic component should be captured and displayed in a salient place on the personal homepage to indicate personal competence. In addition, community operators can highlight peer feedback according to different circumstances. For instance, a Q&A community can also offer various ways to increase the possibility of attaining peer feedback, especially for contributions with small feedback.

5.3. Limitations and Research Directions

As with most prior studies, this work also has its limitations which offer opportunities for further exploration. First, although interesting findings have been uncovered, namely, different manifestations of extrinsic motivation have varying effects on intrinsic motivation. However, this paper centers around the panel data collected from a Q&A community, which may, to some extent, hinder the generalizability of the final findings. We call for more research works to generalize the findings or extend the current findings from more different types of virtual community platforms.

Second, most of the available factors in a virtual community have already been considered, but it is still relatively difficult to control the potential external intervention of community-level factors. For instance, it is still difficult to know whether the platform in the period of data collection has some shocks, the process of managing knowledge entropy within virtual communities, or whether there are some special incentive campaigns taking place on the platform [50]. In addition, the knowledge contribution behavior in a virtual community may depend on education and culture. Therefore, we call for future research to investigate how community-level factors and culture-level factors moderate various motivational factors on sustained knowledge contribution by exploring and comparing multiple communities simultaneously if the data are available.

Third, this study employs the number of a member’s newly contributed knowledge to measure sustained knowledge contribution but does not meticulously conceptualize the knowledge contribution as a complex measurement, which may not only include the numbers, but also the quality and expertise. As a matter of fact, in the knowledge-based view of virtual communities, knowledge is the community’s most valuable intangible resource [15,51]. If the knowledge contributed fails to reflect sufficient quality and accuracy, then no one will ever use the community again [15]. In other words, those answers with high quality would be more beneficial for communities [6]. To this end, we call for future research to explore how members can generate and contribute knowledge that is more valuable to a community.

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