Which Positive Feedback Matters? The Role of Language Concreteness and Temporal Effect in Continuous Contribution in Open Innovation Community

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Abstract

The feedback mechanism is the basis for motivating users to make continuous contributions in the Open Innovation Community (OIC). Although previous studies have revealed the overall role of positive feedback in promoting continuous user contribution, it is not clear which type of positive feedback is more effective and how it changes over time. To solve these problems, we constructed a research model based on reinforcement theory and took Lego Ideas, a typical OIC, as the research object to crawl users' ideas and feedback data for empirical analysis. The results confirmed the effect of positive feedback and further demonstrated that, the effectiveness of positive feedback varies based on feedback concreteness and the tenure of the focal user. Our study contributes to the literature on how feedback affects user contributions in online communities by refining the classifications of feedback, and provide practical guidance for companies to motivate users to contributing ideas continuously.

Keywords: Open Innovation Community, Continuous Idea Contribution, Positive Feedback, Feedback Concreteness, Time Effect

Introduction

In the tide of the digital economy, users are becoming an important source of enterprise value (Leeflang, 2011; Wang et al., 2021). Enterprises are scrambling to build Online Innovation Communities (OICs) for collaborative innovation and crowdsourcing to serve new product development and the transformation of their innovation systems. Firm-hosted OICs are typically IT-driven open innovation platforms for enterprises. Created through the application of Web 2.0 technologies, OICs are used by companies to obtain user perspectives and product ideas, and to achieve value co-creation with users for product innovation. Many companies have achieved success in applying OICs to obtain user ideas for new product development, such as Idea Storm community of Dell, Lego Ideas community of Lego, and Idea Exchange community of Salesforce. Through OIC, users propose ideas or improve others' ideas, meanwhile, enterprises obtain and integrate users' ideas to understand users' needs more accurately and improve the quality of new product development.

Previous studies have pointed out that users' continuous innovation is essential to the development of OIC (Dong et al., 2020, 2023; Zhang et al., 2022). However, user innovation contribution in OIC usually decreases over time (Huang et al., 2014), how to motivate users' continuous innovation contribution is particularly important. In OIC, the feedback mechanism is key to sustaining user participation (Wang et al., 2021). On the one hand, feedback is the evaluation of user idea quality by OIC members, which facilitates focal users to identify innovation problems and directions for improvement, at the same time, influences their self-efficacy and self-satisfaction, further stimulating their willingness to innovate (Liao et al., 2021). On the other hand, feedback enables focal users to acquire knowledge in product and technology owned by others through establishing direct connections with community members, ultimately enhancing their ability to innovate. The enhancement of innovation willingness and ability, in turn, affects users' subsequent innovation contribution behavior (Mustafa et al., 2022; Wang et al., 2022).

Most previous studies have focused on the influence of structural features of feedback (e.g., quantity, frequency, timeliness, etc.) (Chan et al., 2015; Chen et al., 2012), as well as the source features of feedback (e.g., peer/firm feedback, feedback credibility, etc.) (Wang et al., 2018; Wang et al., 2021), and relatively little research has been conducted on the content of feedback, especially lacking a discussion of cognitive dimensions (e.g., concreteness) (Wang et al., 2022). Moreover, the existing literature has mainly focused on the holistic role of feedback and has not fully considered how the impact of feedback on users' contribution behavior changes over time. In reality, users may contribute to the community for several years and may receive a great deal of feedback at various points in their tenure. In the context of our study, users are exposed to feedback with predominantly positive comments, and it remains to be studied whether receiving positive comments repeatedly for a long period of time leads to a diminished effect of positive feedback.

Combining the above theoretical and practical backgrounds, this paper focuses on 1) how the cognitive dimension of positive feedback - concreteness affects the relationship between positive feedback and users' continuous idea contribution behavior, and 2) how the impact of positive feedback on users' continuous idea contribution behavior changes as users' time in the community grows. Based on relevant research on feedback and reinforcement theory, this paper takes feedback concreteness and user tenure as moderating variables, and investigates how the impact of positive feedback on users' continuous idea contribution changes through regression analysis, with Lego Ideas community users as research subjects. The positive impact of positive feedback on users' continuous idea contribution was found to be positively moderated by feedback concreteness while negatively moderated by user tenure. In terms of theoretical contributions, this paper finds that users are sensitive to the degree of concreteness of positive feedback content, but long-term positive feedback has saturation effect. The results highlight the importance of feedback concreteness and the temporal effects of positive feedback, enriching the research on how feedback affects user contributions in the context of online communities and providing practical guidance for companies to effectively use feedback mechanisms to motivate users' continuous idea contributions.

Literature Review

Continuous Contribution in OICs

The literature on online user behavior identifies a variety of factors that influence user contribution behavior, including enjoyment (Wasko and Faraj, 2005), expertise (Zhu et al., 2017), self-image (Chen et al., 2018), and reputation (Liao et al., 2013). However, the antecedents of continuous and initial contributions may differ, as factors that emerge after the first contribution of an idea may influence a user's decision to continue participating (Zhang et al., 2013). Therefore, previous studies have also investigated the factors influencing the continuous idea contribution of OIC users and have indicated that such factors can generally be identified from three perspectives: psychological, functional and social (Fang and Zhang, 2019). The psychological dimension refers primarily to personal motivation, which can be further divided into intrinsic (e.g., self-efficacy and learning) and extrinsic (e.g., extrinsic rewards) motivation (Dong et al., 2020). For example, Liao et al (2013) found that both hedonic and utilitarian motivations were positively related to the willingness to contributing continuously, and the former was more important. A study by Wan and Cheng (2016) also found that internal and external motivations significantly influenced users' willingness to contribute behavior, which in turn acted on users' continuous contribution behavior. The functional dimension generally refers to the various types of mechanisms of the platform (Jian et al., 2019), as well as the perceived satisfaction of participants with the attributes of the platform (Liu et al., 2020), which can influence their continuous idea contribution behavior. For example, Qin and Liang (2017) studier and emphasized the important role of community user identification mechanisms on users' active and reactive contribution behaviors. In addition, social dimensions mainly include reciprocity (Guan et al., 2018), social identity (Dong et al., 2020), and community response or interaction (Chen et al., 2012; Yan and Jian, 2017). Specifically, Zhou et al. (2020) highlighted that social identity and community influence can effectively motivate users' knowledge sharing behavior in OIC; Chan et al. (2015) pointed out that peer-to-peer and peer-to-firm interactions can significantly influence users' continuous idea contribution behavior. Feedback is usually included in user interactions, and its related studies will be reviewed in detail in the next section. Overall, given the importance of users' continuous idea contribution behavior to OIC operations, its antecedent research has important academic value and practical significance.

Feedback in OICs

Feedback mechanisms are widely used in OIC to influence the behavior of individuals, and previous studies have shown that feedback plays an important and basic role in promoting users' continuous idea contributions in OICs. On the one hand, feedback helps recipients to evaluate their own creativity, which affects their self-efficacy and self-satisfaction and acts on their subsequent contribution willingness and behavior (Jabr et al., 2014; Phang et al., 2015). On the other hand, feedback also provides guidance to help recipients correct their own mistakes and understand community preferences, which in turn influence their subsequent idea contribution ability (Huang et al., 2019).

Table 1 summarizes some of the relevant studies on feedback and user contribution. Most studies on feedback emphasized the structured features of feedback, for example, Chen et al. (2012) explored the impact of the amount and timeliness of feedback on users' idea contributions and sustained engagement. Meanwhile, some scholars have classified feedback in terms of source, separately examining the impact of peer feedback and firm feedback on users' continuous idea contributions. Besides, the valence of feedback, i.e., positive and negative feedback, has received considerable attention, such as positive feedback, which is believed to increase contributors' sense of self-efficacy and trust, thus facilitating their future contributions (Guan et al., 2018; Shriver et al., 2013). Conversely, negative feedback indicates disapproval or disagreement with the contributed knowledge, which may disappoint the recipients and hinder their confidence in subsequent contributions (Chen et al., 2019). In addition, the expression form of feedback also played an important role, as Wang et al. (2022) found that positive textual feedback was positively correlated with users' sustained contributions, while positive non-textual feedback (likes) showed a significantly opposite effect.

In general, the relevant literature has extensively discussed the structural features of feedback (e.g., quantity, frequency, timeliness, etc.), but relatively little research has been conducted on the specific content of feedback (e.g., language use). The literature on online communities points out that there are two main aspects of language use by users when expressing their personal opinions, one being the cognitive aspect and the other being the emotional aspect (Peng et al., 2020). First, the cognitive aspect of language refers to its degree of concreteness, since the evaluation of idea can be expressed in a concrete or abstract way. In this paper, language concreteness is defined as the degree of descriptiveness and exactness provided by the feedback content about the object of evaluation (Hansen and Wänke, 2010; Peng et al., 2020). For example, "Your spaceship is well designed" and "Great job" can express the feedback provider's positive assessment of the creator, but the latter is applicable to a variety of ideas while the former is more specific and realistic. The impact of feedback with different levels of concreteness on users' continuous ideas contribution behavior remains to be studied. Second, the emotional aspect of language usually refers to its affective tendency (positive/negative), and as mentioned above, positive and negative feedback has been categorized and studied by scholars. Meanwhile, under the realistic background of OIC, positive feedback accounts for the vast majority of peer feedback, with only a few neutral or negative feedbacks, so this paper focuses on positive feedback and focuses on the cognitive aspects of its language use.

In addition, the extant literature has mainly explored the holistic role of feedback, and there is a lack of research on the temporal effects of feedback. Specifically, community users may contribute to the community for several years and may receive significant positive feedback at various points in their tenure.

	Dependent variables		Feedback features					
	Contribution	Continuous contribution	Numbers	Speed	Length	Source	Emotion	Concreteness
Chen et al. (2012)	√		√	√				
Chan et al. (2015)	√					√		
Wang et al. (2018)		√	√					
Ogink and Dong (2019)	√				√	√	√	
Guan et al. (2018)		√	√					
Zhou et al. (2020)	√		√					
Dong et al. (2020)		√	√					
Chan et al. (2021)	√				√	√	√	
Wang et al. (2022)		√					√	
This research		√					√	√

Table 1. Part of the Research on Feedback and User Contribution

In this case, it is not yet clear whether the impact of positive feedback on users' continuous idea contributions changes over time. Previous studies have pointed out that users' tenure reflects their loyalty to the community and can influence their future behavior (Dong et al., 2020). Riedl and Seidel (2018) also emphasized that users' tenure variables are effective in capturing the effects caused by the passage of time and therefore are often included as control variables in studies related to online communities to eliminate time effects (McSweeney, 2004), and empirical results similarly demonstrated a significant correlation between user online time and community contribution (Wang et al., 2021). Therefore, it is valuable to examine the changing role of positive feedback on user contributions over different points of users' tenure. In general, this paper focuses on the effect of positive feedback, exploring how the role of positive feedback on users' continuous idea contributions is influenced by the concreteness of the feedback, and the temporal effect of positive feedback on users' continuous idea contributions, i.e., how the role changes over time as users join the community.

Theoretical Basis and Hypotheses Development

Reinforcement Theory

Reinforcement theory is a popular theory of motivation that is widely used in management practice. The central principle of the theory is that an individual's behavior is a function of outcomes. Positive or desirable outcomes reinforce the behavior and increasing its subsequent frequency, while negative or undesirable outcomes discourage the behavior and reduce its frequency (Stajkovic and Luthans, 1997; Richardson, 2013). Stimuli used to increase desired behavior are referred to as positive reinforcers (e.g., money), whereas dissuasive stimuli are referred to as negative reinforcers (e.g., punishment) (Richardson, 2013). Stajkovic and Luthans (2003) identified three main reinforcers that can influence an individual's behavior, namely, monetary rewards, feedback, and social recognition. Specifically, feedback refers to information about the individual's performance and the evaluation of the performance of the task; social recognition refers to attracting the individual's attention through the use of words (e.g., expressions of praise, interest, etc.) (Stajkovic and Luthans, 2003). Reinforcement theory suggests that the utility of reinforcers depends on several factors, such as the duration of reinforcement, the frequency of reinforcement, and the importance and its change of the reinforcer (Bhattacharyya et al., 2020; Richardson, 2013).

In the context of OICs, positive feedback from peers not only contains an evaluation of idea, but also conveys others' praise for the focal user, possessing the characteristics of a reinforcer. For community members, receiving positive feedback from others after posting ideas is expected to reinforce their idea contribution behavior. Previous research thus discussed the role of positive feedback as a reinforcer and explored its timeliness (Camacho et al., 2019), frequency (Guo et al., 2018), and other characteristics (Wang et al., 2022; Zhu et al., 2019). Differently, this study focuses on the importance of positive feedback with different levels of concreteness to users, as well as changes in the importance of positive feedback over time. Specifically, we analyzed the moderating effect of feedback concreteness and user tenure on the relationship between positive feedback and users' continuous idea contribution behavior.

Hypotheses Development

Positive feedback in this paper refers to the behavior that community users in OIC give positive comments to other users' ideas, which is a public appreciation and recognition of the recipient's ideas (Ji et al., 2022; Qin and Liang, 2017). As an important reinforcer, positive feedback, on the one hand, can provide others' evaluation of idea and information on how to improve, stimulating individuals' future idea contribution behavior through the result effect and information content. On the other hand, the expectation of gaining recognition and reputation is one of the main motivations for users to participate in the community. After users submit their ideas, positive feedback can express peer recognition, which in turn can influence their future idea contribution behavior by satisfying their motivation (Chen and Hung, 2010). Compared with the reinforcer of monetary rewards, the information and reputational value of positive feedback is more practical and effective for most OIC users. The literature on reputation research also points out that reputation rewards are more effective than money in stimulating user contributions (Chen et al., 2012; Jeppesen and Frederiksen, 2006). In addition, studies on user-generated content (UGC) have shown that positive feedback, especially in the form of text comments, satisfies users' internal and external motivations to drive their continuous content contributions (Wang et al., 2022). For example, Chen et al. (2019) argue that receiving more textual feedback from their community peers can promote users' content contribution in online communities, and strengthen the positive effect of non-textual feedback as well. In the context of this paper, positive feedback recognizes the value of users' ideas and provides positive reinforcement for their idea contributions, thus serving as a motivating factor for future idea contribution behaviors. Therefore, we hypothesize that:

H1: Positive feedback has a positive impact on users' continuous idea contribution behavior.

Research in reinforcement theory states that feedback as a reinforcer can be conveyed in different forms and ways, but to work better it needs to be 1) operationalized as an external intervention, 2) conveyed in a positive way, 3) immediate, and 4) specific (Stajkovic and Luthans, 2001). In the context of this study, users received positive feedback on their ideas from other members of the community, mostly occurring in the period after the ideas were posted. The concreteness of the feedback, however, depends on the language used by the commenter. Feedback concreteness refers to the extent to which the feedback content provides descriptive and specific information about the subject of the evaluation (Peng et al., 2020). It has been noted that concrete language gives more realistic judgments than abstract language (Hansen and Wänke, 2010) and is more persuasive in shaping attitudes and behaviors (Larrimore et al., 2011). In OICs, as opposed to abstract positive feedback (e.g., "Great idea"), concrete positive feedback (e.g., "The color of your idea matches well") can provide useful information value to the focal user while expressing recognition and praise. This allows users to learn which features are popular and to obtain insight into other ways they can improve. As a result, users gain a sense of self-efficacy while also improving their ability to post ideas, and thus are more likely to contribute ideas in the future. Furthermore, it has been noted that, unlike the value of money, which is measured in terms of quantity, the value of social recognition focuses more on their content. Using noncontingent standardized phrases (e.g., "Good job!") fails to show individuals how much their idea is valued through social recognition (Stajkovic and Luthans, 2003). Because such recognition is indiscriminate, applies to any other person, and differs from true recognition (Stajkovic and Luthans, 2001). In this study, abstract positive feedback suffers from the problem of indiscrimination, while concrete positive feedback brings users more realistic evaluation and recognition, better social interaction experience and more useful information value. Reinforcement theory suggests that the importance of the reinforcer is an important factor in its utility. It is obvious that concrete positive feedback is more important to users than abstract positive feedback, and thus has a stronger effect on their continuous idea contribution behavior. Therefore, we hypothesize that:

H2: Feedback concreteness has a positive moderating effect on the relationship between positive feedback and users' continuous idea contribution behavior. Specifically, the higher the degree of feedback concreteness, the stronger the positive influence of positive feedback on users' continuous idea contribution behavior.

To explain the changes in OIC users' contribution behavior after exposure to large amounts of positive feedback, we need to understand how the role of social reinforcers changes with repeated applications. In this regard, previous research has shown that as reinforcers are reoccurring, their reinforcing effect on individual behavior diminishes (McSweeney, 2004). This phenomenon is also known as reinforcer saturation. Overexposure of reinforcers can lead to a decrease in their value until they no longer have a motivational effect (Bhattacharyya et al., 2020). Therefore, repeated receipt of the same reinforcer may not result in an increase in individual behavior. Experimental studies in human behavior have also shown that social reinforcers (e.g., praise and recognition) tend to lose their effectiveness when they are repeated or prolonged (Erickson, 1962; Gewirtz and Baer, 1958). Similarly, this paper holds that the saturation effect of reinforcement theory is also applicable to the research context of online user behavior. As users join the community for a longer period of time, they will not only receive repeated positive feedback in their own ideas, but will also be exposed to a large amount of positive feedback in the process of browsing others' ideas. The overexposure of positive feedback results in a decrease in its motivational effect on users' idea contribution behavior. Overall, when users are repeatedly exposed to a large amount of positive feedback, it will become less important to them, especially indiscriminate abstract positive feedback, which in turn leads to a weakened reinforcing effect of positive feedback on users' continuous idea contribution. Thus, we hypothesize that:

H3: User tenure has a negative moderating effect on the relationship between positive feedback and users' continuous idea contribution behavior. Specifically, the longer the user

tenure, the weaker the positive effect of positive feedback on users' continuous idea contribution behavior.

Methods

Data Collection

The data in this paper comes from the typical open innovation community Lego Ideas, which was founded in April 2014 as a platform for global Lego fans to publish product ideas. Registered members of the community can submit and publish their personal product ideas, as well as view, favor and comment on others' ideas. Works that receive more than 10,000 favors will have the opportunity to be reviewed and put into production. Up to 2021, Lego Ideas has attracted more than 1 million registered users and collected more than 30,000 original models.

In this paper, a crawler written in Python was used to randomly capture 23,983 users of the Lego Ideas community. In order to better examine the effect of positive feedback over time as users join, and to ensure the timeliness of the data, users who joined the community in 2019 were selected. We then crawled all ideas posted by the above users from January 2019 to December 2020 and all comments left by other members, including the ideas' title, description and submission time, the number of comments, comment content, and comment time, etc. After data cleaning, we constructed a panel dataset with a time window of calendar months, and a total of 4,980 ideas from 1,983 users and 39,110 comments were retained.

Variables Measurement

Dependent Variable

The dependent variable in this paper is the continuous idea contribution of users. Drawing on previous studies (Ogink and Dong, 2019; Yang and Han, 2021), the number of ideas posted by user i in month t is used to measure the continuous idea contribution of users, denoted as $Contribution_{it}$.

Main Research Variables

The independent variable of interest in this study is positive feedback. To measure this variable, we first apply a natural language processing technique, the Vader package in Python 3.7, to evaluate the feedback content and obtain an emotional tendency score for each feedback (Wang et al., 2022), where -1 represents negative, 1 represents positive, and 0 represents no significant emotional tendency. Thereby, we classify each peer feedback as positive, negative or neutral. Then positive feedbacks are selected as our study object, and the number of positive feedbacks received by user i in month t is recorded and noted as $Positive\_feedback_{it}$.

In addition, this study attempts to reveal the moderating role of the cognitive features of feedback language (i.e., feedback concreteness) in the relationship between positive feedback and users' continuous idea contribution. To measure the concreteness of the feedback content, this paper refers to the method of Peng et al. (2020) and uses the dictionary of concreteness ratings to score the feedback content. The dictionary, designed specifically to measure linguistic concreteness and integrated via Internet crowdsourcing, includes nearly 40,000 common English words and expressions (Brysbaert et al., 2014), and its reliability and validity have been demonstrated by its creators and subsequent applied studies (Peng et al., 2020; Ransbotham et al., 2019). Specifically, we first split each feedback into words, and then divide the sum of the concreteness scores of the words in the feedback by the total number of words in the feedback to obtain the concreteness score for each feedback. The average concreteness score of all feedback received by user i in period t was used to measure the feedback concreteness variable, denoted as $Concreteness_{it}$.

To test the time effect of positive feedback affecting users' continuous idea contributions, this paper empirically tests user tenure as a moderating variable. User tenure is an important factor influencing user contributions and is often included in models of studies related to user behavior in online communities to control for changes in users over time as they joined the community (Chan et al., 2015; Chen et al., 2019). Following a related approach by Camacho et al. (2019), we added the interaction term of user tenure and positive feedback in the regression equation to test whether the role of positive feedback changes as users' tenure in the community grows. In this paper, user tenure specifically refers to the number of months from user i's registration to period t, denoted as $Tenure_{it}$.

	Variables	Measures
DV	$Contribution_{it}$	The number of ideas posted by user i in period t.
IV	$Postive\_feedback_{it}$	The number of positive feedback received by user i in period t.
Moderator	$Concreteness_{it}$	The average concreteness score of positive feedback received by user i in period t.
	$Tenure_{it}$	Number of months from registration to period t for user i.
Controls	$Tenure^2_{it}$	The square of the number of months from registration to period t for user i.
	$Experience_{it}$	Total number of ideas posted by user i since registration up to period t.
	$Feedback\_length_{it}$	The average length of comments received by user i in period t.
	$Firm\_feedback_{it}$	The number of official comments received by user i in period t.

Table 2. Description of the Main Variables

Variables	N	Mean	Std. Dev.	Min	Max
$Contribution_{it}$	47592	0.105	0.525	0	27
$Postive\_feedback_{it}$	47592	0.807	5.521	0	315
$Concreteness_{it}$	47592	0.219	0.629	0	4
$Tenure_{it}$	47592	7.364	6.582	0	23
$Experience_{it}$	47592	1.370	3.100	0	132
$Feedback\_length_{it}$	47592	1.256	4.826	0	135
$Firm\_feedback_{it}$	47592	0.054	0.352	0	18

Table 3. Descriptive Statistics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	VIF
(1) $Contribution_{it}$	1.000							-----
(2) $Postive\_feedback_{it}$	0.416	1.000						1.38
(3) $Concreteness_{it}$	0.495	0.393	1.000					2.19
(4) $Tenure_{it}$	-0.043	-0.011	-0.043	1.000				1.10
(5) $Experience_{it}$	0.422	0.307	0.267	0.252	1.000			1.38
(6) $Feedback\_length_{it}$	0.323	0.342	0.714	-0.035	0.207	1.000		2.06
(7) $Firm\_feedback_{it}$	0.297	0.402	0.215	-0.006	0.406	0.194	1.000	1.35

Table 4. Correlation Coefficients

Control Variables

Drawing on relevant studies of online user behavior (Chan et al., 2021; Dong et al., 2020; Zhou et al., 2020), this paper first controls for the experience of users posting ideas ($Experience_{it}$) and adds a quadratic term for user tenure ($Tenure^2_{it}$). Second, the average length of all peer feedback received by users is controlled ($Feedback\_length_{it}$). Finally, considering the impact of firm feedback on users' idea contribution, the number of firm feedback is controlled ($Firm\_feedback_{it}$).

Table 2 and Table 3 shows the description as well as the descriptive statistics of each variable.

In addition, correlation analysis and multi-collinearity test were performed in this paper, and Table 4 reports the result. The correlation coefficients among all variables are lower than 0.8, and the variance inflation factor (VIF) ranged from 1.10 to 2.19, all lower than 3, indicating that we don't need to worry about the problem of multi-collinearity.

Estimation Model

This study aims to investigate the impact of positive feedback on users' continuous idea contribution, and the moderating effect of the feedback concreteness as well as the user tenure. The OLS estimator is widely used due to its blue (best linear unbiased estimator) property. Therefore, we employ a fixed effects OLS regression of panel data for the empirical study. To address potential problems in estimation, this paper considers the following points in the model design process: first, the estimated model may face potential reverse causality problems, as the number of idea contributions may affect the number of positive feedbacks received during the same observation period. We thus lagged the independent and control variables by one period to mitigate this potential endogeneity problem. Second, the regression model for panel data requires a choice between fixed effects (FE) and random effects (RE) models, and this paper confirmed by Hausman test (chi^2 = 7359.62, p<0.001) that the fixed effects model is the better choice. Third, this paper applies robust standard errors in the estimation model to deal with potential heteroscedasticity, autocorrelation, and overdispersion problems. The final estimation model is developed as follows:

$$\begin{aligned} Contribution_{it} = {} & \beta_1 Positive\_feedback_{i,t-1} + \beta_2 Concreteness_{i,t-1} + \beta_3 Positive\_feedback_{i,t-1} \\ & * Concreteness_{i,t-1} + \beta_4 Positive\_feedback_{i,t-1} * Tenure_{i,t-1} + \beta_5 Tenure_{i,t-1} \\ & + \beta_6 Controls_{i,t-1} + u_i + v_t + \varepsilon_{it} \end{aligned}$$

where each variable is defined as described above. $Controls_{it-1}$ represents the control variables, u_i and v_t represent dummy variables for individual fixed effects and month fixed effects, respectively, and ε_{it} is the error term. In this paper, we are primarily interested in β1, β3, and β4 to verify the effect of positive feedback on users' continuous idea contribution and how this effect is influenced by feedback concreteness and the users' tenure.

Data Analysis and Results

Hypothesis Test

In this paper, data analysis was conducted with Stata 15.1, and Table 5 shows the fixed effects regression results. Model 1 contains only control variables, Model 2 adds independent variables to base model, Models 3 and 4 add feedback concreteness and user tenure, respectively, and their interaction terms with positive feedback. Model 5 is the full model. As shown, the adjusted R^2 increases from 0.178 in model 1 to 0.374 in model 5, which proves that the explanatory power of the model is relatively good.

Hypothesis 1 explores the impact of positive feedback on users' continuous idea contribution. As shown in model (2) of Table 5, the number of positive feedbacks received by users has a significant positive effect on the number of their subsequent idea contributions (Coef = 0.038, p < 0.01). The result supports H1, which supposes the positive feedback received by users promotes subsequent idea contributions. According to reinforcement theory, positive feedback, as a positive reinforcer, can satisfy users' motivation of expecting attention and support after posting ideas, thus motivating them to continue contributing ideas. Besides recognition, positive feedback also brings suggestions from community peers, providing users with knowledge about creating ideas and further driving the behavior of contributing ideas.

Hypotheses 2 and 3 explore the moderating effect of feedback concreteness and user tenure on the relationship between positive feedback and users' continuous idea contribution. The results of model (3) in Table 5 show that the higher the degree of feedback concreteness, the stronger the positive relationship between positive feedback and continuous idea contributions from users (Coef = 0.022, p < 0.05), which supports hypothesis 2. Conversely, the results of model (4) in Table 5 show that the longer the duration of user tenure, the weaker the positive relationship between positive feedback and users' continuous idea contribution (Coef = -0.001, p < 0.05), and hypothesis H3 is also supported. According to reinforcement theory, the importance of the reinforcer is a critical influencing factor in the utility of reinforcement. For users, concrete feedback not only provides evaluations and recognition that feel more authentic, but also offers valuable information about community preferences and knowledge related to idea creation. Abstract feedback, however, provides only indiscriminate recognition and is less important. Therefore, feedback concreteness can positively moderate the relationship between positive feedback and users' continuous creative contribution. The more specific the positive feedback, the stronger the positive effect on the user's continued creative contribution. Moreover, the importance of reinforcers decreases with recurrence, and the longer a user's tenure in the community, the more positive feedback he or she is exposed to. Positive feedback is less important to users than when they are new to the community, and its reinforcement is less effective. Therefore, user tenure can negatively moderate positive feedback and user's continuous contribution behavior. For users who have joined the community for a long time, the positive effect of positive feedback on the continuous thought contribution behavior of users is weaker than that of users who have joined the community for a short time.

	M1	M2	M3	M4	M5
Postive_feedback		0.038*** (0.008)	-0.0096 (0.009)	0.048*** (0.008)	-0.013 (0.009)
Concreteness			0.328*** (0.021)		0.318*** (0.018)
Tenure				-0.044*** (0.003)	-0.024*** (0.003)
Postive_feedback Concreteness*			0.0224** (0.009)		0.031*** (0.008)
Postive_feedback Tenure*				-0.001** (0.001)	-0.002*** (0.000)
Tenure²	0.001*** (0.000)	0.001*** (0.000)	0.0006*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Experience	0.051*** (0.011)	0.046*** (0.012)	0.037*** (0.013)	0.052*** (0.012)	0.044*** (0.012)
Feedback_length	0.027*** (0.002)	0.018*** (0.002)	0.0075*** (0.001)	0.017*** (0.002)	0.008*** (0.001)
Firm_feedback	0.148 (0.085)	0.028 (0.090)	0.034 (0.096)	0.033 (0.089)	0.039 (0.096)
Intercept	0.060*** (0.006)	0.051*** (0.007)	0.030*** (0.006)	0.047*** (0.007)	0.026*** (0.006)
Monthly dummies	Yes	Yes	Yes	Yes	Yes
Observations	47,592	47,592	47,592	47,592	47,592
R-squared	0.178	0.275	0.361	0.285	0.374
# of users	1,983	1,983	1,983	1,983	1,983
F	103.43	87.35	116.02	105.37	131.08
Notes: Robust standard errors in parentheses. * p < 0.1; ** p < 0.05; *** p < 0.01.					

Table 5. Regression Results

Robustness Checks

To ensure the robustness of the study results, some additional analyses were conducted in this paper. First, using alternative models to analyze the data is an effective way to test robustness (Dong et al., 2020). Considering that the dependent variable is a count variable, we have used a Poisson model for estimation.

	(1)	(2)	(3)	(4)	(5)	(6)
Postive_feedback	0.058*** (0.002)	0.084*** (0.012)			0.036*** (0.008)	-0.008 (0.008)
Postive_percent			0.673*** (0.038)	0.792*** (0.053)		
Concreteness		1.865*** (0.025)		-0.074 (0.054)		0.313*** (0.019)
*Postive_feedback * Concreteness*		0.023*** (0.007)		0.105** (0.053)		0.028*** (0.008)
*Postive_feedback * Tenure*		-0.001*** (0.000)		-0.028*** (0.003)		-0.002*** (0.000)
Tenure	-0.072*** (0.008)	-0.082*** (0.010)	-0.029*** (0.003)	-0.013*** (0.002)	-0.072*** (0.007)	-0.032*** (0.005)
Tenure^2	0.001*** (0.000)	0.002*** (0.001)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Comments			0.029*** (0.007)	0.012** (0.005)		
Experience	0.028*** (0.003)	0.013*** (0.002)	0.038*** (0.013)	0.042*** (0.012)	0.018*** (0.002)	0.018** (0.007)
Feedback_length	0.088*** (0.002)	0.009*** (0.002)	0.007*** (0.001)	0.008*** (0.001)	0.011*** (0.002)	0.006*** (0.001)
Firm_feedback	0.171*** (0.017)	0.058*** (0.015)	0.032 (0.096)	0.020 (0.094)	-0.065** (0.030)	-0.073** (0.028)
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47,592	47,592	47,592	47,592	29,760	29,760
# of users	1,983	1,983	1,983	1,983	1,240	1,240
R-squared			0.346	0.398	0.251	0.359
F			120.95	138.91	52.24	86.14
Log likelihood	-9467.209	-5579.169				
Wald chi^2	4627.77***	8040.60***				
Notes： Robust standard errors in parentheses. * p < 0.1; ** p < 0.05; *** p < 0.01.						

Table 6. The Estimation Results of Robustness Checks

The results are shown in columns (1) and (2) of Table 6 and are consistent with the findings of this paper. Second, since the vast majority of feedback is positive in this research context, the total number of feedbacks received by users is not controlled in the initial model for avoiding the problem of multi-collinearity. For robustness, we add the total number of feedbacks received by users as a control variable in the model, while replacing the measurement of the independent variable. With reference to Chan et al. (2021), we measured the independent variable as the proportion of positive feedback received by user i in period t to the total number of feedbacks. The results are shown in columns (3) and (4) of Table 6, and the consistency of the results further demonstrates the robustness of our findings. In addition, this paper conducted additional regression analysis by randomly selecting subsamples, and the results are shown in columns (5) and (6) of Table 6, which remain consistent with the initial results. The above analysis shows the robustness of the regression analysis in this paper.

Discussion

Based on reinforcement theory, this paper investigates the effect of positive feedback on users' continuous idea contribution behavior in OIC, and focuses on the moderating effects of feedback concreteness and user tenure. By conducting a regression analysis of real data in a typical OIC, the results of the study found that positive feedback can exert a reinforce effect and promote users' continuous idea contribution behavior. Moreover, feedback concreteness played an important positive moderating role between positive feedback and users' continuous idea contribution behavior, i.e., the reinforcing effect of concrete positive feedback was stronger. User tenure, on the other hand, has a negative moderating effect between positive feedback and users' continuous idea contribution behavior, suggesting that there is a time effect of positive feedback, and its motivating effect on users diminishes as the time they join the community grows.

The research in this paper has some theoretical and practical implication. In terms of theoretical contributions, first, previous studies on the content of feedback have tended to focus on the emotional aspects of feedback, and there is a lack of research on the cognitive aspects. This paper refines the classification of feedback by exploring the degree of concreteness of feedback content, pointing out two types of feedback (abstract/concrete) in OIC, and emphasizing the importance of concrete feedback to users. Our research deepens the study of user innovation from a social interaction perspective and complements the understanding of the role of different types of feedback. Second, existing studies highlight the positive role of feedback based on self-efficacy, yet do not consider changes in its positive effect. Based on the saturation effect in reinforcement theory, this paper analyzes the process by which the positive effects of peer feedback diminish over time due to changes in its importance, providing a fine-grained understanding of how peer feedback affects user contributions. This study's discussion of the differences in the reinforcement utility of positive feedback and the changes provides a new perspective on the study of user behavior in online communities.

Practically, this paper also has implications for how online communities take full advantage of peer feedback to motivate user contributions. First, given the reinforcing effect of positive feedback, community managers should increase their efforts to encourage peer feedback. For example, adopting badge rewards to incentivize users to provide feedback on others' ideas, setting up special evaluators for ideas, or building automatic comment mechanisms to leverage the motivating effect of positive feedback on user contributions. Second, community managers should provide guidance for the content of feedback, reminding feedback providers to point out the concrete excellence of ideas in the comment, rather than abstract indiscriminate praise. Finally, the community should adopt differentiated feedback mechanisms for new and old users. For example, increasing the exposure of new users' ideas to attract more peer feedback; while for experienced users, the abstract positive feedback they receive should be appropriately folded and then highlight those concrete feedbacks. Filtering invalid feedback and setting up other incentives, such as holding creative events that require users to meet certain qualifications to participate, create a good community atmosphere for users' creative contributions.

There are also certain limitations in this paper. First, the data in our study derive from a single platform during a particular time period, which resulting in limited generalizability of the findings. Future studies are expected to further expand the sample to validate that the results are specific or general. Second, the concreteness of each feedback is rated according to the concreteness dictionary, which has the shortcoming of not being able to understand specific contexts. A combination of manual labeling and machine learning or generative AI can be considered in the future to classify the feedback from the sentences-level and further validate the findings of this paper. Third, our study mitigates the impact of individual characteristics through fixed effects, but does not consider the potential influence of commenter, which is worth exploring in future research.

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References

Bhattacharyya, S., Banerjee, S., Bose, I., and Kankanhalli, A. 2020. "Temporal Effects of Repeated Recognition and Lack of Recognition on Online Community Contributions," *Journal of Management Information Systems* (37:2), pp. 536–562.

Brysbaert, M., Warriner, A. B., and Kuperman, V. 2014. "Concreteness Ratings for 40 Thousand Generally Known English Word Lemmas," *Behavior Research Methods* (46:3), pp. 904–911.

Camacho, N., Nam, H., Kannan, P. K., and Stremersch, S. 2019. "Tournaments to Crowdsource Innovation: The Role of Moderator Feedback and Participation Intensity," *Journal of Marketing* (83:2), pp. 138–157.

Chan, K. W., Li, S. Y., Ni, J., and Zhu, J. J. 2021. "What Feedback Matters? The Role of Experience in Motivating Crowdsourcing Innovation," *Production and Operations Management* (30:1), pp. 103–126.

Chan, K. W., Li, S. Y., and Zhu, J. J. 2015. "Fostering Customer Ideation in Crowdsourcing Community: The Role of Peer-to-peer and Peer-to-firm Interactions," *Journal of Interactive Marketing* (31:1), pp. 42–62.

Chen, C.-J., and Hung, S.-W. 2010. "To Give or to Receive? Factors Influencing Members' Knowledge Sharing and Community Promotion in Professional Virtual Communities," *Information & Management* (47:4), pp. 226–236.

Chen, L., Baird, A., and Straub, D. 2019. "Why Do Participants Continue to Contribute? Evaluation of Usefulness Voting and Commenting Motivational Affordances within an Online Knowledge Community," *Decision Support Systems* (118), pp. 21–32.

Chen, L., Marsden, J. R., and Zhang, Z. 2012. "Theory and Analysis of Company-Sponsored Value Co-Creation," *Journal of Management Information Systems* (29:2), pp. 141–172.

Chen, W., Wei, X., and Zhu, K. X. 2018. "Engaging Voluntary Contributions in Online Communities: A Hidden Markov Model," *MIS Quarterly* (42:1), pp. 83-100.

Dong, L., Hou, J. (Jove), Huang, L., Liu, Y., and Zhang, J. 2023. "Impacts of Normative and Hedonic Motivations on Continuous Knowledge Contribution in Virtual Community: The Moderating Effect of Past Contribution Experience," *Information Technology & People* (ahead-of-print: ahead-of-print).

Dong, L., Huang, L., Hou, J. (Jove), and Liu, Y. 2020. "Continuous Content Contribution in Virtual Community: The Role of Status-standing on Motivational Mechanisms," *Decision Support Systems* (132), p. 113283.

Erickson, M. T. 1962. "Effects of Social Deprivation and Satiation on Verbal Conditioning in Children," *Journal of Comparative and Physiological Psychology* (55:6), pp. 953–957.

Fang, C., and Zhang, J. 2019. "Users' Continued Participation Behavior in Social Q&A Communities: A Motivation Perspective," *Computers in Human Behavior* (92), pp. 87–109.

Gewirtz, J. L., and Baer, D. M. 1958. "Deprivation and Satiation of Social Reinforcers as Drive Conditions," *The Journal of Abnormal and Social Psychology* (57:2), pp. 165–172.

Guan, T., Wang, L., Jin, J., and Song, X. 2018. "Knowledge Contribution Behavior in Online Q&A Communities: An Empirical Investigation," *Computers in Human Behavior* (81), pp. 137–147.

Guo W., Wang Y., Liang R., Zheng Q., Qiu Z., and An W. 2018. "Study on Factors of Individual Innovation Contribution Degree Based on User Feedback in Open Innovation Communities," *Science & Technology Progress Policy* (35:03), pp. 146–152.

Hansen, J., and Wänke, M. 2010. "Truth from Language and Truth from Fit: The Impact of Linguistic Concreteness and Level of Construal on Subjective Truth," *Personality and Social Psychology Bulletin* (36:11), pp. 1576–1588.

Huang, N., Burtch, G., Gu, B., Hong, Y., Liang, C., Wang, K., Fu, D., and Yang, B. 2019. "Motivating User-Generated Content with Performance Feedback: Evidence from Randomized Field Experiments," *Management Science* (65:1), pp. 327–345.

Huang, Y., Vir Singh, P., and Srinivasan, K. 2014. "Crowdsourcing New Product Ideas Under Consumer Learning," *Management Science* (60:9), pp. 2138–2159.

Jabr, W., Mookerjee, R., Tan, Y., and Mookerjee, V. S. 2014. "Leveraging Philanthropic Behavior for Customer Support: The Case of User Support Forums," *MIS Quarterly* (38:1), pp. 187–208.

Jeppesen, L. B., and Frederiksen, L. 2006. "Why Do Users Contribute to Firm-Hosted User Communities? The Case of Computer-Controlled Music Instruments," *Organization Science* (17:1), pp. 45–63.

Ji H., Qi G., and Liang Y. 2022. "Are Actions More Powerful than Words? —User Interaction and Continuous Contribution of User Idea Updates," *Management Review* (34:04), pp. 80–89.

Jian, L., Yang, S., Ba, S., Lu, L., and Jiang, L. C. 2019. "Managing the Crowds: The Effect of Prize Guarantees and in-Process Feedback on Participation in Crowdsourcing Contests," *MIS Quarterly* (43:1), pp. 97–112.

Larrimore, L., Jiang, L., Larrimore, J., Markowitz, D., and Gorski, S. 2011. "Peer to Peer Lending: The Relationship Between Language Features, Trustworthiness, and Persuasion Success," *Journal of Applied Communication Research* (39:1), pp. 19–37.

Leeflang, P. 2011. "Paving the Way for 'Distinguished Marketing'," *International Journal of Research in Marketing* (28:2), pp. 76–88.

Liao, C., To, P.-L., and Hsu, F.-C. 2013. "Exploring Knowledge Sharing in Virtual Communities," *Online Information Review* (37:6), pp. 891–909.

Liao, J., Chen, J., and Mou, J. 2021. "Examining the antecedents of idea contribution in online innovation communities: A perspective of creative self-efficacy," *Technology in Society* (66), p. 101644.

Liu, X., Min, Q., and Han, S. 2020. "Understanding Users' Continuous Content Contribution Behaviours on Microblogs: An Integrated Perspective of Uses and Gratification Theory and Social Influence Theory," *Behavior & Information Technology* (39:5), pp. 525–543.

McSweeney, F. K. 2004. "Dynamic Changes in Reinforcer Effectiveness: Satiation and Habituation Have Different Implications for Theory and Practice," *The Behavior Analyst* (27:2), pp. 171–188.

Mustafa, S., Zhang, W., and Naveed, M. M. 2022. "What Motivates Online Community Contributors to Contribute Consistently? A Case Study on Stackoverflow Netizens," *Current Psychology* (42:13), pp. 10468-10481.

Ogink, T., and Dong, J. Q. 2019. "Stimulating Innovation by User Feedback on Social Media: The Case of an Online User Innovation Community," *Technological Forecasting and Social Change* (144), pp. 295–302.

Peng, C.-H., Yin, D., and Zhang, H. 2020. "More Than Words in Medical Question-and-Answer Sites: A Content-Context Congruence Perspective," *Information Systems Research* (31:3), pp. 913–928.

Phang, C. W., Kankanhalli, A., and Tan, B. C. Y. 2015. "What Motivates Contributors vs. Lurkers? An Investigation of Online Feedback Forums," *Information Systems Research* (26:4), pp. 773–792.

Qin M., and Liang S. 2017. "Study on User Recognition Mechanism and Contribution Behavior in Online Innovation Communities: Based on Prosocial Behavior Theory," *Nankai Business Review* (20:03), pp. 28–39.

Ransbotham, S., Lurie, N. H., and Liu, H. 2019. "Creation and Consumption of Mobile Word of Mouth: How Are Mobile Reviews Different?" *Marketing Science* (38:5), pp. 773–792.

Richardson, K. M. 2013. "Reinforcement theory," *Encyclopedia of management theory* (E. H. Kessler, Ed.). Thousand Oaks: SAGE, pp.655-660.

Riedl, C., and Seidel, V. P. 2018. "Learning from Mixed Signals in Online Innovation Communities," *Organization Science* (29:6), pp. 1010–1032.

Shriver, S. K., Nair, H. S., and Hofstetter, R. 2013. "Social Ties and User-Generated Content: Evidence from an Online Social Network," *Management Science* (59:6), pp. 1425–1443.

Stajkovic, A. D., and Luthans, F. 1997. "A Meta-Analysis of the Effects of the Oranizational Behavior Modification on Task Performance," *Academy of Management Journal* (40:5), pp. 1122–1149.

Stajkovic, A. D., and Luthans, F. 2001. "Differential Effects of Incentive Motivations on Work Performance," *Academy of Management Journal* (44:3), pp. 580–590.

Stajkovic, A. D., and Luthans, F. 2003. "Behavioral Management and Task Performance in Organizations: Conceptual Background, Meta-Analysis, and Test of Alternative Models," *Personnel Psychology* (56:1), pp. 155–194.

Wan L., and Cheng H. 2016. "Research on Motivation of Users' Continuous Knowledge Contribution Behavior in Virtual Knowledge Community Based on Self-determination Theory," *Information Science* (34:10), pp. 15–19.

Wang, N., Liu, Y., and Xiao, S. 2022. "Which Feedback Matters? The Role of Expressions and Valence in Continuous High-quality Knowledge Contribution in the Online Q&A Community," *Decision Support Systems* (156), p. 113750.

Wang T., Qi G., Zhang Y., and Liang Y. 2018. "Research on Continuous Knowledge Sharing Behavior in Open Innovation Communities," *Information Science* (36:02), pp. 139–145.

Wang, X., Lu, J., Ow, T. T., Feng, Y., and Liu, L. 2021. "Understanding the Emotional and Informational Influence on Customer Knowledge Contribution through Quantitative Content Analysis," *Information & Management* (58:2), p. 103426.

Wasko, M. M., and Faraj, S. 2005. "Why Should I Share? Examining Social Capital and Knowledge Contribution in Electronic Networks of Practice," *MIS Quarterly* (29:1), pp. 35-57.
Yan, B., and Jian, L. 2017. "Beyond Reciprocity: The Bystander Effect of Knowledge Response in Online Knowledge Communities," *Computers in Human Behavior* (76), pp. 9–18.
Yang, M., and Han, C. 2021. "Stimulating Innovation: Managing Peer Interaction for Idea Generation on Digital Innovation Platforms," *Journal of Business Research* (125), pp. 456–465.
Zhang, C., Hahn, J., and De, P. 2013. "Continued Participation in Online Innovation Communities: Does Community Response Matter Equally for Everyone?" *Information Systems Research* (24:4), pp. 1112–1130.
Zhang, J., Qi, G., Song, C., and Chen, J. 2022. "Continuous Idea Contribution in Open Innovation Communities: The Role of Verbal Persuasion from Peers," *Frontiers in Psychology* (13), p. 1061415.
Zhou T., He L., and Deng S. 2020. "Research on the Factors Affecting Users' Knowledge Sharing in Open Innovation Communities," *Journal of Modern Information* (40:03), pp. 58–64.
Zhu, H., Kock, A., Wentker, M., and Leker, J. 2019. "How Does Online Interaction Affect Idea Quality? The Effect of Feedback in Firm-Internal Idea Competitions," *Journal of Product Innovation Management* (36:1), pp. 24–40.
Zhu, J. J., Li, S. Y., and Andrews, M. 2017. "Ideator Expertise and Cocreator Inputs in Crowdsourcing-Based New Product Development," *Journal of Product Innovation Management* (34:5), pp. 598–616.