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What motivates online community contributors to contribute consistently? A case study on Stackoverflow netizens

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Abstract
Online Question and answer (Q&A) communities are the common and famous platforms to learn and share knowledge and are very useful for every knowledge seeker. Less knowledge contribution is a critical issue for the sustainability and future of these platforms. The motivation of inactive users to participate in Q&A communities is a real challenge. Based on the social cognitive and social exchange theory, we have studied the knowledge contribution patterns of active and consistent StackOverflow users over the last eleven years. We have used a difference generalized method of moments estimator to estimate the proposed model. Results revealed that reciprocation of knowledge and social interaction positively, whereas knowledge seeking of active and consistent users negatively influences knowledge contribution. Peer recognition and repudiation have partially positive and negative effects on users' knowledge contribution. This research offers theoretical and practical suggestions to encourage people to contribute their knowledge to online Q&A communities.

Keywords Q&A communities · Knowledge contribution · GMM · Active users · Inactive users

Introduction

Online Question and answer communities (Q&A) are unanimously gaining popularity in all fields of life. A common person can solve problems, acquire knowledge, share ideas, and express their feelings or experience about some place or thing. Particularly these communities help those looking for the answers to their technical queries and seek guidance in their practical workplace.

Q&A communities have become popular in the workplace because of their ease of use and speed of response. The modern age of technology has reshaped and restructured how people study and share information. Meaningfully, the COVID-19 epidemic reaffirmed the value of Q&A communities by significantly increasing the need for online knowledge exchange (Vaughan, 2020). Online resources make it possible for anybody, at any time, to find information on almost any topic. A broad spectrum of people, from beginners to experts, may benefit from internet resources, which provide a vast range of information in simple and understandable terms. Q&A sharing websites like Stack Overflow, Quora, Ask Ubuntu, SuperUser, and Yahoo! Answer are examples of commonly used Q&A communities.

An online Q&A community's users are vital components, and their active engagement is essential to the community's growth and development. Apart from the benefits and low cost of acquiring knowledge, these communities face a severe issue of low participation. Users of these communities acquire knowledge and hesitate to contribute knowledge. A decreasing trend in knowledge sharing has also been observed among the most active users of Stackoverflow (Graph 1). It reflects that over some time, knowledge contribution decrease. As a result, many Q&A groups are grappling with the issue of how to encourage members to keep contributing to the body of knowledge (Chen et al., 2021; Dong et al., 2020). To determine what elements influence users' willingness to engage in community activities, particularly knowledge contribution, it is necessary to identify these factors (Guan et al., 2018. Understanding the strategies that keep participants engaged and address the wide range

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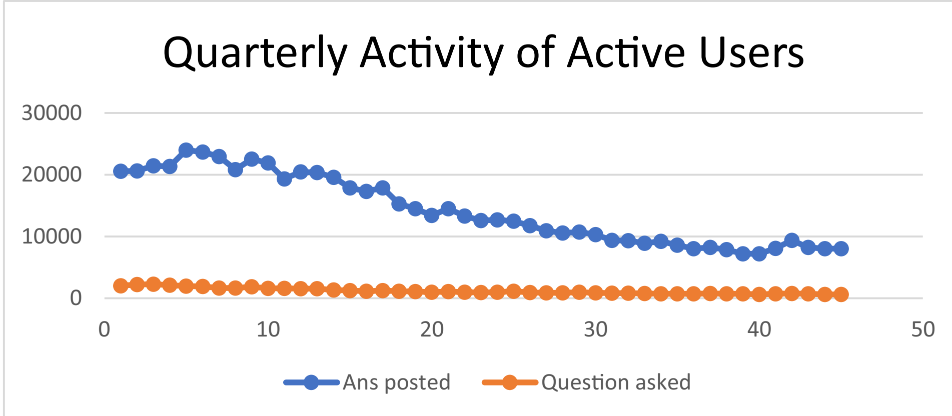

Graph 1 Questions and answers contributed

of motives across time and participant types is helpful in stimulating inactive users.

To remain operational, Q&A websites must rely on the continual voluntary contribution of their users when all users do not contribute adequately to online knowledge-sharing communities, particularly those focused on practical knowledge structure and distribution in the technical background. The ability of these communities to survive can be jeopardized. The phrase "tragedy of the commons," coined by (Hardin, 1968), describes the situation in online knowledge-sharing groups. According to this concept, many users choose to take a free journey or contribute insufficiently rather than consistently participating in an online knowledge-sharing community that is open and freely accessible to anybody.

StackOverflow is one of the leading Q&A communities that serve sixteen million[1] registered users to search for knowledge and provide an opportunity to contribute their knowledge. It has gained widespread popularity among enthusiast programmers and professionals since its launch in 2008. Stackoverflow data for 2020 revealed that only 6.07% of users actively participate[1] at StackOverflow, even though most community members are inactive yet offer some knowledge.

Previous studies have identified that knowledge-seeking has a positive (Chen et al., 2021; Guan et al., 2018) or no impact (Chen et al., 2019; Wang et al., 2022) on knowledge sharing. Self-interest and prosocial motivation have also significantly affected continuous knowledge contribution (Dong et al., 2020). Furthermore, peer repudiation has a negative (Wang et al., 2022) or positive (Chen et al., 2019) impact on knowledge sharing. Hence, it needs to be further explored to understand the contribution of these factors toward users' knowledge sharing.

Researchers have rarely investigated the subject to our knowledge that thoroughly investigated the knowledge sharing behaviour of *consistent and active users* for a long period and applied its results to solve the issue of low user participation. Hence the following research question is presented to study.

RQ. What motivates online community users to contribute *consistently*?

There is an essential need to investigate the motivational factors behind the continuous participation of users and replicate the same for the rest of the community members to enhance their participation. For this purpose, we have selected StackOverflow and picked users who participated at least quarterly and asked a question, answered a question, or posed a comment once quarterly. We have tracked the activities of these pioneer users from 2010 to 2020 and applied the generalized method of moments (GMM) panel data model to check the impact of their different activities on their knowledge contribution. The study results can solve the most important practical problem of less contribution by considering the influential factors and their effect on users' knowledge contribution. Results revealed that knowledge-seeking as a question posted, peer recognition as upvotes, and peer repudiation as peeve votes negatively influence active users of StackOverflow to share knowledge. Whereas reciprocation as answer received, social interaction as comment received, peer precogitation as favourite votes, and peer repudiation as downvotes positively influence active users to contribute knowledge.

Theoretical foundation

There are two commonly known and recognized ways of knowledge sharing, face to face and online. Face-to-face knowledge sharing usually requires the physical presence of participants at the time of knowledge sharing. In contrast, the latter does not need a physical presence at the same time

[1] https://stackoverflow.com/users?tab=Reputation&filter=all.

to interact. Virtual interaction is enough in online knowledge sharing. The process of managing knowledge includes the sharing of existing knowledge. The act of exchanging one's knowledge (skills, information, or expertise) with other individuals, whether they are family members, classmates, friends, members of a community (such as Stackoverflow), or members of the same or other organizations, is an activity known as "knowledge sharing" (Serban & Luan, 2002). It creates a bridge between individual and corporate knowledge, which boosts absorptive and innovative ability and ultimately results in a sustainable competitive advantage for both people and businesses (Dalkir, 2013).

There are increasing practical and academic issues for the majority of online Q&A communities as a result of the declining interaction and information sharing. As a result, previous research on internet knowledge sharing has focused on the social strategies that encourage involvement in online communities and information sharing. Many academics have frequently established the theoretical foundation to explain the knowledge contribution and users' participation in online Q&A communities using social cognitive and social exchange theories. These theories help underlie the theoretical foundation to investigate and explore the factors behind users' continuous participation.

Social cognitive theory

Miller and Dollard (1941) social learning theory believes that witnessing how others behave in social situations may impact one's thoughts, feelings, and behaviours. Social cognitive theory (SCT), which is derived from social learning theory, uses a triadic reciprocal model to describe human behaviour where environment, personal characteristics (such as cognition), and actions all interact with one other to explain human behaviour (Bandura, 1986). Based on this theory, learning may be seen as information processing in which past experiences and environmental cues function as expressions and guide future action. Gaining social recognition is a key driver of knowledge sharing in online Q&A groups because user connections are mostly weak linkages to gain meaningful information. As a result, the participants may learn from the feedback they get from society about the relevance of certain participation behaviours and may further change their subsequent participation practices to respond to the general demand (Shi et al., 2021). SCT shows that people practice actions similar to those rewarded because they believe they will lead to a favourable result (Bandura, 1986).

Similarly, in online Q&A groups, we regard the responses that get the most votes as modelled answers. We'd look at how these responses function as precursors to community contributions to knowledge. We interpret community feedback as a set of behaviour outcomes that serve as an encouragement (social reward, as indicated by SCT) to encourage participants to execute what they have learned through previous experience or see others perform what they have contributed and learned. In the context of social cognition theory, self-efficacy and outcome expectancies are two essential variables that relate to an individual's confidence in his capacity to effectively conduct action and the chance that an individual's activity may lead to a given result, respectively (Anderson et al., 2007). Prior studies also explained that group size, social learning, and peer recognition impact users' knowledge contribution (Jin et al., 2015). As a result, earlier online Q&A community contributions might influence future contributions. Affective and vicarious learning is used in SCT to examine the influence of earlier actions on future knowledge contributing behaviours.

Social exchange theory

Information sharing is a social interaction emphasized by economic exchange theory (Liu et al., 2005). Extrinsic incentives focus on the economic exchange theory, while intrinsic rewards focus on the social exchange theory. An individual's actions are influenced by the outcomes of his analysis of the advantages and sacrifices he receives and makes when he engages in a certain activity. As long as the advantages outweigh the costs, people are more likely to act. Previous research has shown a link between good corporate knowledge management and incentive systems. Extrinsic motivations, such as money or promotion prospects, encourage employees to share their expertise to gain an advantage in the workplace (Gee & Young-Gul, 2002). Unspecified commitments that cannot be defined as a tangible medium of exchange are the main focus of social exchanges. In online Q&A communities, intrinsic rewards are common instead of extrinsic ones, and participants reciprocate their knowledge when they receive sufficient intrinsic rewards. As a result, social transaction tends to foster sentiments of belonging, personal duty, appreciation, trust, and loyalty (Jin et al., 2015). When it comes to online social Q&A groups, knowledge and attention are two of the most common exchangeable products. In online social media, attention has become a rare commodity. Thus those who give information expect to get knowledge or attention as compensation (Jin et al., 2015). Hence social exchange theory is used to understand the knowledge exchange of participants in the context of their group interaction.

Research model & hypothesis development

We establish a research model to guide our academic inquiry into the relationship between motivating elements on Q&A websites and user knowledge engagement with the

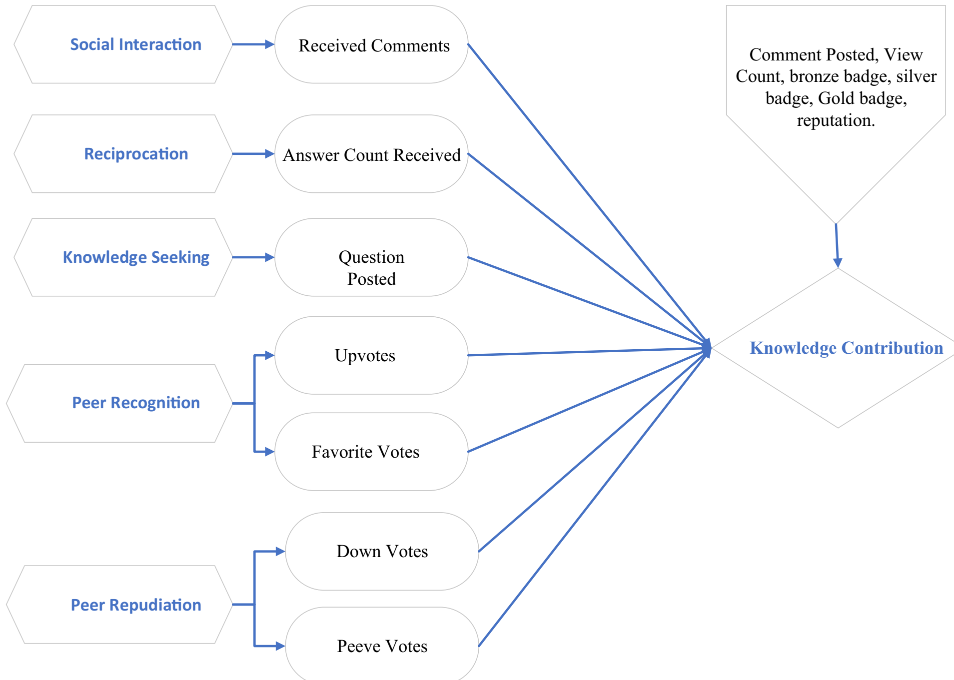

Fig. 1 Conceptual framework

theoretical backdrop stated previously. The following is a suggested study framework that incorporates user-generated questions, commenting, and voting procedures to shed light on the diversity in each user's internet-based knowledge sharing behaviour (Fig. 1). For example, it is anticipated that the incentive elements supplied by a single user's Question, response, upvoting, and favourite votes all contribute to knowledge sharing. In contrast, it is believed that peeve voting and downvoting are inversely related to knowledge contribution. Fellow users provide feedback since it is predicted that internet-based communication promotes individual knowledge exchange.

Commenting effect on knowledge contribution

Public cooperation in the form of comments amongst online colleagues is a critical component of the success of an internet-based platform. The distinction between commenting and voting is interconnected; the former serves as a communication and collaborative problem-solving route, while the latter serves as a mechanism for collaborative motivation or demotivation to stimulate actions. The internet-based social platform's reward and reputation algorithmic mechanism facilitates this. It's well accepted that the individual psyche may have a beneficial or detrimental impact on an individual's self-worth, capacity to communicate successfully with others, and ability to prosper in a work environment (Wiegand & Geller, 2005; Guan et al., 2018) found that online users' knowledge contribution is favourably influenced by social feedback. Chen (2019) argues that the conversation about the authenticity and reliability of contributed knowledge moulds users' perception and, ultimately, their motivation for committed contribution in an internet-based context. They also discovered that favourable remarks motivate knowledge contributors to do their best work. According to current research, community interaction strongly motivates participants to participate in web knowledge-sharing networks (Chang & Chuang, 2011). However, researchers still need to fully investigate the role of comments in encouraging involvement in an online system. This study exclusively investigates the comments received by users and their impact on the knowledge contribution of active users in StackOverflow. The number of comments received might indicate how connected users are to the community and how frequently they collaborate with peers on a web-based knowledge-sharing platform. As much as a user gets comments from other community members, it demonstrates that s/he is becoming more engaged with the community and interested in addressing issues (Tajfel & Turner, 1986; Burke et al., 2009) found that new users who received a reaction from their peers encouraged them to contribute to a web-based news platform. Through social interaction, peers may support and appreciate one other's accomplishments or criticize the irrelevant and low-quality knowledge contributed to the community (Liao et al., 2020). With this discussion, we hypothesize that.

H1: Peer comments influence active users' knowledge contribution.

Effect of a question asked on knowledge contribution

Q&A community users' main interaction at the community platform is asking questions or providing answers. We believe that when participants ask questions at the community platform, they expect to receive appropriate answers to resolve their issues. Once users receive their desired answer, they can either be quiet or reciprocate and help others solve their issues. Either way, the Question asked impacts participants' knowledge contribution. According to (Hsu et al., 2007), there is a strong correlation between the willingness to share information and personal result expectations. According to (Huysman, 2002), the need for knowledge or information might be proved subjectively and objectively. It's possible to interpret an entity's need for information to indicate their "objective reality," which drives them to seek the information they need to reach a decision or solve a problem. So, public Q&A societies provide members with a channel to identify their need for information, explain the request in clear language, and work together to get answers that meet the need for knowledge. A strong correlation exists between a person's self-perception of their ability to provide information and their share amount (Hao et al., 2019). Individuals join online communities, particularly social Q&A platforms, because they want to learn new things or seek answers to their questions. In online knowledge-sharing networks, norms of reciprocity have a substantial impact on knowledge contribution (Guan et al., 2018; Simon & Tossan, 2018) claim that user pleasure from the community drives them to become committed community members, encouraging them to respond to the community by providing trustworthy and authentic information. Knowledge demands greatly influence participants' behaviour toward traditional web-based social Q&A communities (Fang & Zhang, 2019). Hence, we hypothesize that.

H2: Online participants' knowledge-seeking affects their knowledge contribution.

Positive and negative voting effects on knowledge contribution

In the context of online Q&A communities, motivational variables such as positive (upvotes, favourite votes) and negative (Down and peeve votes) voting are intrinsic since the user or recipient of these votes does not get any monitory paybacks. In online communities where people share information and expertise, voting is an important way to gauge how much confidence other members have in a user's knowledge and how much they depend on their answer to their issue. As a result of web-based involvement, a user's perception of ability, pleasure, and acknowledgement of capabilities might be adopted as hopeful psychological repercussions due to the irredeemable positive and negative votes obtained. A study by (Chen et al., 2019) found that positive votes had a beneficial impact on knowledge contributors, whereas negative votes had a negative impact on knowledge contributors. More contributions to online knowledge communities are encouraged by accumulating positive and negative votes from other users. It increases the knowledge contributor's feeling of self-efficacy, competence, and responsibility and encourages them to contribute even more in the future.

On the other hand, negative feedback or penalty diminishes intrinsic motivation (Deci et al., 2001), who found positive incentives to be more motivating than negative ones. Users who obtain constructive utility votes from web-based platforms are encouraged to share their expertise. Still, those who receive many negative votes are demoralized and lose their intrinsic desire (Lou et al., 2013; Mustafa et al., 2022b). According to (Jin et al., 2015), Peer recognition is positively associated with online Q&A group behaviour in terms of knowledge contribution. This discussion leads us to hypothesize.

H3: More upvotes received by online users from other community members make them conscious, and they care about their reputation in the community and contribute accurate and quality knowledge.
H4: Peers' favourite votes motivate users to contribute more knowledge to an online knowledge-sharing community.
H5: Downvotes by online peers affect the motivation of online knowledge contributors motivation and knowledge contribution.
H6: Peeve votes from fellow users negatively affect active users' motivation to share knowledge on online platforms, and they share less.

Answer received effect on knowledge contribution

Seeking information and contributing knowledge at Q&A communities is two-way traffic. Users ask questions at Q&A communities and resolve their problems. Answers from fellow users help them solve their problems. In the response, they feel in debt to the community and respond to other users' questions. Sense of reciprocation influences users to participate more and more. Reciprocity can never be one way (Mustafa et al., 2022a, b; Wiertz & de Ruyter, 2007). A feeling of duty is fostered through reciprocity, which results in mutual benefit. It's important to note that achieving what you desire may not always lead to reciprocal actions; as soon as individuals have what they want, their inclination to respond to things decreases (Liao et al., 2020). Those who place a high value on reciprocity feel that they will

Table 1 Description of variables

Variable Type	Variable	Definition
Explained variable	Knowledge contribution(Quantity)	"Number of overall answers the focal user X contributed to the online community in a given time t."
	Knowledge contribution (Quality)	"Number of answers the focal user X contributed to the online community in a given time t that has received peer recognition and endorsement."
Exploratory variables	Received comments	"Number of comments the focal user X receives in a given time t for questions and answers submitted to the community."
	Question asked	"Number of questions asked by a focal user X in a given time t."
	Favourite votes	"The number of favourite votes (Accepted by Originator + favourite) received by a user X in the given time t for a question or Answer posted in the community."
	Upvotes	"Number of upvotes the focal user X receives in a given time t for questions and answers submitted to the community."
	Peeve votes	"Number of peeve votes (offensive + close + deletion + spam) received by the focal user X in a given time t for his question and answers submitted to the community."
	Downvotes	"Number of downvotes the focal user X receives in a given time t for Q&A submitted to the community."
	Answer count received	"Number of answers the focal user X receives from the community in a given time t."
Control variables	View count	"The number of users seen the question asked or answered by a focal user X in a given time t."
	Badges	Gold badges. "Number of gold badges granted to the focal participant by the community in a given time." Silver badges. "Number of silver badges granted to the focal participant by the community in a given time." Bronze badges. "Number of bronze badges granted to the focal participant by the community in a given time."
	Reputation	"Reputation score of the focal participant in the community at the beginning of every quarter."
	Comment posted	"Number of comments posted by the focal user X in a given time t."

improve their mutual ties by doing so (Zhao et al., 2016). The hope of giving and taking increases the drive to give something fresh. People contribute their expertise to social Q&A groups because they believe they will get help if they need it. Consequently, answering their questions should influence their information searching and knowledge contribution under theories on social exchange and social reciprocity. So we hypothesize that.

> H7: More answers received by users influence them to contribute more to Q&A communities.

Control variables

We have incorporated some control factors in our study to analyze the knowledge contribution better. We used reputation earned by a user in the community, view count they receive for their questions and answers, badges earned on the successful continuous participation, and comments posted by them on peer posts. These variables are dependent on users' main activities. Reputation is calculated by the cumulative score of all endogenous variables discussed above. View count refers to the number of peers who read your answer or Question regardless of other activities. Badges is a Q&A community mechanism of reward to motivate users' participation based on their contribution. Comments posted to peer posts can help us understand the pattern of user interaction. Researchers have explored that reputation and badges influence the knowledge contribution behaviour of users (Chen et al., 2021). View count is also influential in knowledge contribution to online health communities (Alasmari & Zhou, 2019). Table 1 presents the description of variables used in the study.

Methodology

Active user

Keeping in view the nature of online platforms, we have set our criteria for selecting active users quarterly. We assume that as this platform does not pay any extrinsic benefits to its users and users contribute voluntarily, we define an active user who at least asked a question, provided an answer, or wrote a comment every three months. The reason behind selecting the most active and consistent users is that if we

Table 2 Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Answer Posted	13,376	47.332	101.192	0	1999
Question Posted	13,376	3.878	8.835	0	233
View Count	13,376	19266.526	117546.11	0	6,264,869
Received Comments	13,376	85.245	211.765	0	5745
Comment Posted	13,376	127.429	255.057	0	3214
Answer Count Received	13,376	7.339	20.97	0	731
Bronze Badge	13,376	5.593	14.515	0	334
Silver Badge	13,376	7.024	17.222	0	1019
Gold Badge	13,376	0.774	1.758	0	33
Upvotes	13,376	282.516	753.908	0	14,076
Down Votes	13,376	4.116	6.897	0	85
Favorite Votes	13,376	29.994	60.606	0	1311
Peeve Votes	13,376	0.071	0.834	0	71
Reputation	13,376	4152496.8	11,185,875	-172	2.180e+08

study the pattern of knowledge sharing of consistent and active users and replicate the same model on inactive users, then the issue of low participation can be solved properly.

Data collection

We have taken data from the StackOverflow dump data file 2021 and transformed it. We used the MySQL framework and Python to handle the data extraction. The initial data is filtered via the use of a SQL query that is conducted on Microsoft SQL Server 2017. The query results are saved in CSV format, and then Pandas is used to load the data from the CSV file into Python. Python is used in the calculation of quarters.

Sample collection

We have collected balanced panel data for the last eleven years. To exclusively focus on the active users' activities on the platform, we first identify the active users and then extract their activities for the last eleven years. We define active users who participated each quarter from January 2010 to December 2020. 304 users were identified out of the 199,190 registered users who least posted a question, provided an answer to a question, or wrote a comment quarterly from 2010 to 2020.

Identified 304 users who have posted 633,109 answers and asked 51,872 questions between January 2010 till December 2020. We have tracked their User id along with a quarterly number of answers Posted, Questions asked, view count, received comments, comments posted by the user, answer count received, Badges earned (Bronze, silver, Gold), Votes received (Upvotes, Downvotes, Favorite votes, peeve votes), and reputation. A total of 13,376 observations were analyzed for 44 quarters starting from 2010 (Table 2).

The quarterly activity of the sample used in this study is explained in the form of Questions asked and answers posted on the community platform. Although the users selected for our study have been active users in the community for more than a decade, their contribution decreases over time. Graph 1 reflects a stable decreasing trend in Questions asked and a sharp decrease in answers posted during the study period. The possible reason behind this decrease can be the changing trend of widely accepted and most used programming languages. In early 2010 java, PHP, and C++, but 2020, JavaScript, and Python are the most used programming languages. With this changing trend, it is understood that experts of these languages used to share more knowledge because peers asked more Questions about Java, PHP, and C++ in 2010 and onwards, but over time, their knowledge became outdated, and they shared less. Another possible reason is that peers ask fewer questions regarding these languages or the topic which used to be the hot topic a decade ago.

Table 3 present the correlation matrix of variables. It reflects that answer posted has a positive and significant correlation with received comments (0.962), comment posted (0.790), bronze badge (0.580), silver (0.546), gold (0.306), upvotes (0.705), down votes (0.652), favorite vote (0.918), and reputation (0.580). Whereas Question posted (-0.101), answer count received (-0.060), and peeve votes (-0.019) were significant but negatively correlated. It reflects a weak significant negative correlation. Correlation may not imply causality. It is not always the case that changes in one variable produce changes in the other just because there is a link between the two variables. The existence of correlations tells us that there is a link between variables; however, this does not always suggest that one variable causes the change in another one (Chen, 2021). In essence, the discovery of a weak correlation that is statistically significant shows that

Table 3 Correlation coefficients

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Answer Posted	1.000													
(2) Question Posted	-0.101***	1.000												
(3) View Count	0.007	0.614***	1.000											
(4) Received Comments	0.962***	-0.017**	0.043***	1.000										
(5) Comment Posted	0.790***	-0.068***	0.021**	0.770***	1.000									
(6) Answer Count Received	-0.060***	0.938***	0.766***	0.010	-0.034***	1.000								
(7) Bronze Badge	0.580***	-0.002	0.005	0.637***	0.604***	-0.004	1.000							
(8) Silver Badge	0.546***	0.059***	0.034***	0.601***	0.511***	0.050***	0.829***	1.000						
(9) Gold Badge	0.306***	0.104***	0.020**	0.347***	0.369***	0.061***	0.729***	0.636***	1.000					
(10) Upvotes	0.705***	-0.065***	-0.006	0.739***	0.699***	-0.046***	0.948***	0.770***	0.686***	1.000				
(11) Down Votes	0.652***	0.059***	0.076***	0.632***	0.664***	0.070***	0.657***	0.559***	0.527***	0.728***	1.000			
(12) Favorite Votes	0.918***	0.003	0.037***	0.938***	0.777***	0.016*	0.700***	0.642***	0.440***	0.785***	0.637***	1.000		
(13) Peeve Votes	-0.019**	0.183***	0.057***	-0.001	-0.007	0.146***	0.014	0.036***	0.040***	-0.013	0.057***	0.000	1.000	
(14) Reputation	0.580***	-0.069***	-0.019**	0.592***	0.651***	-0.058***	0.924***	0.716***	0.717***	0.958***	0.710***	0.669***	-0.010	1.000

*** $p < .01$, ** $p < .05$, * $p < .1$

a specific exposure does have an influence on the outcome variable but that there are other factors that are also key drivers.

Estimation using a GMM dynamic panel

Models of knowledge contribution incorporate variables that are determined endogenously. For instance, if more knowledge contribution results in the sustainability of the Q&A community, then increased knowledge contribution may result in reciprocity. Chen et al. (2019) Observed strongly correlated variables with knowledge contribution in online Q&A communities using OLS. But, OLS has an issue with simultaneity (Pindyck & Rubinfeld, 1981).

Instrumental variable estimation using GMM offers several benefits over more traditional IV estimate methods (2SLS). For example, its control for endogeneity of the lagged explained variable, unobserved panel heterogeneity, omitted variable bias, and measurement errors. GMM provides best estimates when the time (T) is small, cross-sections (N) are large, variables have a linear function relationship, and explained variable is dynamic along with exploratory variables that are not strictly exogenous. This approach is critical because the explained variable's lagged value is included in the exploratory variables, which aids in capturing the dynamic connection. Furthermore, the robustness of the empirical findings produced by the GMM estimator is not dependent on the availability of reliable information about the error term's distribution. Hence, we utilize the (Arellano & Bond, 1991) technique, which may solve the issue via first differentiation, to assure the estimate's quality.

Furthermore, selecting between system and difference GMM model estimators, we have followed the rule of thumb described (Bond, 2002). First, we have estimated scores for ϕ using pooled OLS and LSDV (fixed effect approach). We have considered pooled OLS as an upper-bound and fixed effect as lower-bound estimates than compared the difference GMM estimates with these. Our difference GMM estimates were higher than the lower-bound fixed effect estimates, and difference GMM results suggest that using system GMM may yield little benefit in this case. Hence, we have decided to carry on the difference GMM in our study.

In its broadest sense, the dynamic panel model includes the following that we have used to determine knowledge contribution.

$$l_n Y_{it} = \Phi l_n Y_{it-1} + \beta X'_{it} + (\eta_{it} + \epsilon_{it}) \quad (1)$$

$$\Delta l_n Y_{it} = \Phi \Delta l_n Y_{it-1} + \beta \Delta X'_{it} + \Delta \epsilon_{it} \quad (2)$$

The fixed effect may be eliminated by first differencing the regressors, but the issue of endogeneity remains. The model is derived from Eq. (2) and has the form of

$$\Delta\mu_{it} = \Delta\eta_i + \Delta\epsilon_{it} \tag{3}$$

$$\mu_{it-1} = \left(\eta_i - \eta_i\right) + \left(\epsilon_{it} - \epsilon_{it-1}\right) = \epsilon_{it} - \epsilon_{it-1} \tag{4}$$

Fixed effects assumed constant across periods are no longer included in the calculation. To account for historical changes in the dependent variable, Eq. (2) is used to express any first-differenced lagged differences.

Models are estimated by controlling for first and second-order autocorrelation with a lagged difference of explained variable and endogeneity in the regressors with lagged values of independent variables. A two-step equation method is used to create consistent estimates of the variance-covariance matrix, which is resilient to panel-specific heteroskedasticity and permits a robust evaluation of instrument validity.

We established the following regression model for our study.

$$\begin{aligned}KC_{i,t} &= \alpha KC_{it-n} + RecCom_{i,t}\beta_1 + QPost_{i,t}\beta_2 + FV_{i,t}\beta_3 + UV_{i,t}\beta_4 + PV_{i,t}\beta_5 + DV_{i,t}\beta_6 \\ &+ AnsRec_{i,t}\beta_7 + ComPost_{i,t}\beta_8 + View_{i,t}\beta_9 + BrzBadge_{i,t}\beta_{10} + SilvBadge_{i,t}\beta_{11} \\ &+ Gold\ Badge_{it}\beta_{12} + Rep_{it}\beta_{13} + Qtr_{dummy} + \omega_{it}\end{aligned} \tag{5}$$

KC is a knowledge contributed, $KC_{i,t-n}$ is the lagged value of knowledge contributed by individual i in time t-1. i represents the individual users, β_0 represents the interceptive term vector, t represents the quarters, and $\varepsilon_{i,t}$ represents the random error term and $\omega_{it} : \varepsilon_i + \mu_{it}$. β_1 to β_{14} represents coefficients of independent and control variables. Qtr_{dummy} represent the quarterly dummies.

Empirical results

Based on the estimators mentioned earlier, we have first simulated a difference GMM model for the control variable (M1) and then a combined model (M2), including independent and control variables for the dependent variable knowledge contribution measured by the answer posted by a user. The Hansen J test ensures that the instruments used in each model are valid. The Arellano-Bond test for the first and 2nd order autocorrelation is used to rule out model misspecification in the first differenced errors. Table 4 presents the equation's estimated parameters for knowledge contribution factors in online Q&A communities.

Using the Hansen J test, it is impossible to prove that the over-identification limitations are true in any model studied ($p = 1.00$). Furthermore, the substantial correlation between the first order is shown by p-values provided for AR (1). Still, there is no indication of second-order correlation in the AR (2) p-values. Hence, the test data show that the robust difference GMM specification is correct (Tables 4 and 5).

Table 4 GMM estimation of knowledge contributed by active users at StackOverflow

Dependent Variable: Answer posted				
Robust				
	Model 1		Model 2	
	Coef.	t-value	Coef.	t-value
Explanatory variables				
Question Posted			-0.695***	-73.24
Received Comments			0.302***	2184.66
Answer Count Received			0.051***	9.54
Upvotes			-0.013***	-896.21
Down Votes			1.291***	641.20
Favorite Votes			0.478***	806.21
Peeve Votes			-0.396***	-17.18
Control Variables				
Comment Posted	0.434***	18737.96	0.034***	422.30
View Count	0.003***	61.75	0.006***	30.87
Bronze Badge	0.482***	637.67	-0.596***	-661.54
Silver Badge	0.587***	2255.68	0.102***	523.92
Gold Badge	-5.723***	-1797.60	0.173***	47.51
Reputation	0.002***	-4375.28	0.008***	-271.43
Quarterly Dummies	Yes	Yes	Yes	Yes
Observations (N)	13,775		13,775	
AR 1 (p-value)	-4.82(0.000)		-7.13(0.000)	
AR 2 (p-value)	-1.34(0.179)		-0.38(0.705)	
Hansen test (p-value)	298.33(1.00)		297.21(1.00)	

*** $p < .01$, ** $p < .05$, * $p < .1$

To examine the influence of independent and control variables on knowledge contribution first, we have used overall answers posted by our sample (304 users) as a parameter of knowledge contribution (Table 4). Then we replaced it with those answers that received peer recognition in the form of upvotes or favorite votes (Table 5).

Model 1 in Table 4 indicates that all control variables significantly influence users' knowledge contribution except the gold badge with a negative coefficient. The possible reason behind this is that the gold badge is the highest badge level awarded to the community members for their services. They do not struggle much after accomplishing the highest reward.

Model 2 results in Table 4 indicate that all the variables under study significantly influence online community users' knowledge participation. Question posted, upvote received, and peeve votes have negative coefficients at p level 0.01, implying that these variables negatively affect

Table 5 GMM estimation of quality knowledge contributed by active users at StackOverflow

Dependent Variable: Answer posted (Peer Recognized answers)				
Robust				
	Model 1		Model 2	
	Coef.	t-value	Coef.	t-value
Explanatory variables				
Question Posted			-0.092(0.414)	-0.82
Received Comments			0.261***	307.22
Answer Count Received			0.026(0.626)	0.49
Upvotes			-0.012***	-95.21
Down Votes			1.282***	114.82
Favorite Votes			0.657***	159.24
Peeve Votes			0.421*	1.46
Control Variables				
Comment Posted	0.415***	1414.00	0.031***	62.75
View Count	0.001***	42.16	0.004***	17.42
Bronze Badge	0.579***	83.70	-0.731***	-157.15
Silver Badge	0.623***	442.69	0.113***	92.15
Gold Badge	-8.228***	-219.45	0.324***	11.39
Reputation	0.003***	-491.09	0.006***	-42.09
Quarterly Dummies	Yes	Yes	Yes	Yes
Observations (N)	12,769		12,769	
AR 1 (p-value)	-4.02(0.000)		-6.07(0.000)	
AR 2 (p-value)	-0.83(0.406)		-0.14(0.890)	
Hansen test (p-value)	131.35(1.00)		128.11(1.00)	

*** $p < .01$, ** $p < .05$, * $p < .1$

users' knowledge contribution. In contrast, received comments from peers at answers and questions posted by users, answer count received against their questions, downvotes, and favourite votes by peers motivate them to share more knowledge. Comments received by the peers with their highest t-value seem to be the most concern area by users for sharing knowledge. It supports hypotheses H1 to H7.

Control variables in M2 also reflect the significant influence, except for the bronze model that has negative beta implies that users are not concerned much about the community reward initially. But after spending some time, they want to establish their image as positive and active members of the community and actively participate in knowledge contribution.

In the second step, we have stimulated the same model for quality knowledge contributed by replacing the dependent variable with the number of answers that receive the peer recognition to check the consistency of our model and results and influential factors that impact quality knowledge contribution. Generally, the results are consistent with the results of the previous model except for two variables that are insignificant in the case of quality knowledge contribution.

Discussion

Key findings and theoretical contribution

This study is exclusively conducted to aid in solving the low participation issue in online Q&A communities. For this purpose, we have collected a rich dataset from the dump data file of StackOverflow. We have studied the active and consistent users for eleven years and analyzed their knowledge contribution quality and quantity to conclude better results to help resolve this practical problem. Different justifications were presented for low participation, and researchers have presented various solutions. Still, researchers have not studied the most active and consistent users to solve this practical issue.

We have divided the knowledge shared by users into two parts, i.e., quantity and quality knowledge following early research (Chang & Chuang, 2011; Chen et al., 2019; Lou et al., 2013). First, we have analyzed the overall knowledge contributed by the selected active users for the period of forty-four quarters. Social interaction in the form of comments received (H1) by peers significantly influences active users' knowledge contribution. As much as a user is social and frequently interacts with peers, he contributes more and likes to help others resolve their issues. Social interaction boosts the sense of belonging to the community, unity, and helping others and motivates users to participate more. As we have applied social exchange theory, this phenomenon truly explained the social exchange of knowledge as people from different parts of the world interact, share their problems and mutually solve them by interaction (Emerson, 1976). The findings are consistent with earlier studies (Chen et al., 2021; Liou et al., 2016; Zhang et al., 2019).

We have observed that knowledge-seeking through questions posted (H2) on a community negatively influences users' knowledge contribution. Whenever the users seek answers from the community, they contribute less. They may be busy with their issue during this period or waiting for the community's response to their problem. Another possible reason is that users like to enjoy a free ride or, in other words, well known economic dilemma tragedy of common implies on Q&A community users. They like to receive knowledge but resist sharing and helping others. The findings contradict the researchers' findings that it positively influences knowledge contribution (Chen et al., 2021).

Peer recognition in the form of upvotes (H3) for the work by peers has a negative effect on the active users' knowledge contribution. The possible reason behind this is that when active users receive a lot of upvotes for their contribution to the community, it raises their reputation and self-efficacy. Peers start trusting their work and expect the right and appropriate contribution. It makes users conscious about the reputation in the community, and they share when they are confident that the knowledge will serve the problem and solve the knowledge seeker's issue. Being selective in contribution decreases the overall knowledge contribution. It is against the researcher's findings who studied the online Q&A community (Chen et al., 2019; Dong et al., 2020) and consistent with (Wang et al., 2022), who studied textual feedback and used a dataset of six months. On the contrary, we have studied the active users who contribute consistently. Researchers have also found that when users interact with peers, upvotes negatively affect knowledge contribution because peers' comments let them realize that they need better quality and accurate information (Chen et al., 2019).

Peer recognition as a favourite vote (H4), on the other hand, has a positive influence on active users' knowledge contribution because a favourite vote is granted in response to the knowledge that solves the problem and is helpful for peers. It gives satisfaction, self-confidence and boosts the trustworthiness of the users. It reflects that peers give worth and acknowledge the credibility of the knowledge source. It also gives an advantage to our study results that we deeply study the behaviour against each kind of vote rather than just considering them positive or negative feedback. With this, active users share more valuable knowledge with the community. It is consistent with the earlier researchers (Dong et al., 2020). Furthermore, earlier researchers did not distinguish between the upvotes and favourite votes, downvotes, or peeve votes.

Peer repudiation as downvotes (H5) positively influences the knowledge contribution of active users. When peers downvote active users' knowledge, they take it positively and treat it as a challenge. They learn more and contribute better knowledge because they want to retain their position and image as trusted knowledge contributors. The other reason could be that many users use these platforms to impress potential employers and seek a job. So they do not want to repudiate their reputation as a potential employee for their future job and contribute more to gain their position and status back. Confirm the claim of earlier researchers (Wang et al., 2022), but they compared the textual and nontextual feedback and used a dataset of six months.

Peer repudiation as peeve votes (H6) by peers negatively influences active users' knowledge contribution. It means extremely bad comments and negative dictation demotivate users from contributing. We can say that negativity bias exists in the Q&A community. It means that individuals are more likely to weigh negative things (Rozin & Royzman, 2001) than positive entities, and repudiation demotivates them. It is consistent with the findings of earlier studies that negative votes discourage users from contributing knowledge (Chen et al., 2019), but they treat negative votes as downvotes and do not study the peeve votes.

Reciprocation of knowledge in the form of answer count (H7) also positively influences active users' knowledge contribution. When users receive answers to their problems from the community, they feel indebted and want to return the favour. They want to reciprocate the favour and help others in solving their issue. Sense of commitment, social bonding, and helping others strengthen in members through this act, and they exchange knowledge to help others resolve their issues. It seems a more realistic reflection of herd behaviour to achieve a common goal. Earlier researchers have also identified that sense of reciprocation exists and influences users to contribute (Liao et al., 2020; Luo et al., 2021), but it contradicts other studies that claim it negatively affects the knowledge contribution (Chen et al., 2021; Wasko & Faraj, 2005) or have no effect (Chang & Chuang, 2011; Chen et al., 2019; Wiertz & de Ruyter, 2007).

Control variables incorporated in our study significantly influence active users' knowledge contribution. Comment posted in social interaction has a positive influence, which means social interaction is a two-way process, and both parties take it positively and are influenced by the conversation. View count means how many users have seen your contributed knowledge also gives positive feelings and motivates users to contribute more. Reputation, a mechanism designed by online Q&A communities, serves as a reward for what users perform in the community. A higher reputation reflects the credibility and trustworthiness of a user by peers. As much higher reputation a user has, they are credible to the community. It also has a positive influence on consumers' knowledge contribution. It is consistent with earlier researchers (Chen et al., 2021; Jin et al., 2016) but contradicts (Chang & Chuang, 2011), who do not favour that reputation influences knowledge contribution. Badges offered as a reward in Q&A communities are significant factors behind knowledge contribution, but bronze badges have an inverse relation with knowledge contribution, and silver and gold have a positive influence. Initially, users do not like to interact and share knowledge because they are new to the community and hesitate to share their knowledge and ideas with peers. But later, as they interact with peers, share their ideas and knowledge, and receive positive feedback, they like to share more. It is consistent with the findings of (Chen et al., 2021).

Secondly, we have analyzed the quality knowledge contributed by active users during the past eleven years at StackOverflow. Results presented in Table 5 are alien to the main analysis except for two variables, i.e., Knowledge-seeking and reciprocation, insignificant for quality knowledge contribution. It is because active users keep contributing quality knowledge to the community regardless of the fact that peers reciprocate them or not. This quality of users makes them unique from inactive users. Active users are dedicated to the community and social welfare. They help peers to solve their issues without any return or expectations. It is consistent with previous studies that consider knowledge quality and influential factors behind sharing quality knowledge (Chang & Chuang, 2011; Chen et al., 2019; Wiertz & de Ruyter, 2007).

Practical implication

This study is conducted to improve the low participation of online Q&A community users and yield some practical implications for community managers to improve user participation. Knowledge-seeking trends or topics in the Q&A community, such as Stackoverflow, change frequently. Whenever a new programming language or software is introduced or popularized among programmers (community users), they ask questions about it. The programming industry is a fast-growing industry. Due to the evolution in technology, users quit or contribute less because they have outdated or less knowledge about new technologies. The trend of question topics is also changed, and new experts emerged. Such as, in 2010, the popular programming languages were different than today. Because of this, old users who were experts in some areas of knowledge in the past decrease knowledge contribution because they do not have first-hand knowledge about the issue. Hence, managers need to launch online training sessions to keep them updated.

Social interaction plays a key role in knowledge exchange in Q&A communities. It builds group feelings and sentiments of helping others. As many users interact, as much they share. We suggest that community managers provide a platform for users to share their ideas publicly and let others help them develop their ideas. Potential financers can also be invited to finance individual and collective projects.

As it has been noticed that negativity bias exists in Q&A communities, so to motivate users, managers need to cross-check the peeve votes/ comments before appearing publicly. They also need to highlight peer recognition to balance the effect of peer repudiation.

Success stories need to highlight, and users need to encourage to share their success stories so peers learn from them and frequently interact. Community commitment and social collaboration emerge among them. The theory of herd behaviour also supports this idea and presents that peers are influenced by others and follow the activities (Mattke et al., 2020). According to SCT, dormant users will follow the active and socially rewarded users and treat them as their role models and follow them to achieve their social status and specific goals in a community (Bandura, 1986).

Managers need to track down the users who quit the community or become inactive when they do not receive answers to their questions. They need to address this properly so that they remain active and participate.

No extrinsic reward is available at Q&A communities, and users contribute voluntarily. We suggest community managers introduce competition activities to make communities more attractive and award rewards to winners. We also recommend that Q&A communities invite potential employers to interact with users and create job opportunities for active users so that inactive users come forward and take it as an opportunity and contribute to attracting potential employers.

Limitations and recommendations

Apart from the several practical implications and theoretical contributions, our study has limitations. Firstly we have used StackOverflow as our target community. The behaviour of other community users can fluctuate due to the content contributed to the community (e.g., social commerce sites, quora, yahoo answer, and online health communities). Future researchers can study active and consistent users of other communities and compare the results to resolve the issue of low participation. Secondly, we have selected consistent users from 2010 and did not consider the users after that. Hence users who joined the community later may have a different pattern of sharing knowledge. Future studies can include the users who are new to the community and consistent. Thirdly, users who do not receive appropriate answers from the community and abandon the community need to be studied. As our study revealed the different influences of peer recognition and repudiation, future studies can use different research approaches to explore the phenomena thoroughly. Fourthly we studied the number of positive and negative feedback; future studies can apply sentiment analysis and study the influence of language used in comments and its influence on consumers' engagement with a community. Furthermore, this study did not incorporate participants' personality traits, gender, and age, but they can influence their contribution patterns in different communities. We suggest incorporating personality traits in future studies and analysing the difference between personality traits and their influence on contribution behaviour.

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Data availability Data used in this study can be downloaded from this link data.stackexchange.com.

Declarations

Competing interests The authors declare no conflict of interest.

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