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Research Article

Unveiling the Dynamics of Extrinsic Motivations in Shaping Future Experts' Contributions to Developer Q&A Communities

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Developer question and answering communities rely on experts to provide helpful answers. However, these communities face a shortage of experts. To cultivate more experts, the community needs to quantify and analyze the rules of the influence of extrinsic motivations on the ongoing contributions of those developers who can become experts in the future (potential experts). Currently, there is a lack of potential expert-centred research on community incentives. To address this gap, we propose a motivational impact model with self-determination theory-based hypotheses to explore the impact of five extrinsic motivations (badge, status, learning, reputation, and reciprocity) for potential experts. We develop a status-based timeline partitioning method to count information on the sustained contributions of potential experts from Stack Overflow data and propose a multifactor assessment model to examine the motivational impact model to determine the relationship between potential experts' extrinsic motivations and sustained contributions. Our results show that (i) badge and reciprocity promote the continuous contributions of potential experts while reputation and status reduce their contributions; (ii) status significantly affects the impact of reciprocity on potential experts' contributions; (iii) the difference in the influence of extrinsic motivations on potential experts and active developers lies in the influence of reputation, learning, and status and its moderating effect. Based on these findings, we recommend that community managers identify potential experts early and optimize reputation and status incentives to incubate more experts.

1. Introduction

Developer question and answering (Q&A) communities such as Stack Overflow (SO) are critical online knowledge-sharing platforms [1]. Some developers in these communities ask related technical questions, e.g., coding issues and fixing bugs, while others provide them with answers [2]. These questions and answers can be accessed and reused by all developers to solve various problems in the software lifecycle, including design, development, and maintenance, to improve their working efficiency. As such, these communities are regarded as a hub for collaborative knowledge creation and utilization.

The core value of such communities is primarily determined by the content provided, particularly the answers' quality. The solutions to the most challenging software development questions are typically provided by a small group of developers with great experience and super skills, defined as experts [3]. Hence, experts' continuous contributions are vital to the sustainability and prosperity of these communities.

However, these communities are suffering from a shortage of experts [4]. Losing active experts may lead to the catastrophic failure of such communities. A feasible solution for the shortage of experts is to cultivate more experts. Developers continuously contribute to Q&A communities and eventually become experts. These developers who have the potential to become experts in the future are defined as potential experts. According to Ryan and Deci's [5] self-determination theory (SDT), motivations to encourage developers to participate in the communities can be intrinsic or extrinsic. The former refers to their participation out of self-happiness or satisfaction and interest [6]. The latter refers to their participation due to the possible gain or punishment from incentives.

Community incentives drive developers to contribute continuously by giving them external rewards or honors. Revealing the rules of the influence of the motivations regarding incentive mechanisms on potential experts' contributions can provide insights into optimizing incentives to cultivate more experts.

A growing literature has reported the influence of motivations on the continuous contributions of active developers, including potential experts, to developer Q&A communities. Some of these studies have investigated the impact of multiple motivations, such as badge [7], reputation [8], and reciprocity [9], on active developers' continuous contributions. Furthermore, a few researchers found that the effect of motivations is affected by some factors. Among them, the moderation role of status has attracted much attention [10–12]. Generally, developer Q&A communities grant developers a certain status or position according to their contributions. The change in developers' status may affect the influence of other motivations on their contribution behavior [13, 14].

However, previous findings may not apply to potential experts. As reported in the literature, most active developers do not become experts [9]. Consequently, those results are most relevant to non-experts. In developer Q&A communities, the contribution patterns of potential experts and most active developers are significantly different. Potential experts, on average, contribute much more than most active developers [15]. In addition, potential experts tend to create answers, while most active developers generally seek answers by asking questions [16]. The difference in behavior patterns between the two types of developers indicates that the rules of the influence of extrinsic motivations on continuous contributions vary considerably.

To reveal the rules of the influence of extrinsic motivations on potential experts' continuous contributions in developer Q&A communities, we seek to answer the following three research questions.

RQ1: What is the Relationship between Extrinsic Motivations and the Sustained Contribution of Potential Experts in Developer Q&A Communities?

Though we know the influence of some extrinsic motivations on active developers' contribution to developer Q&A communities, their impact on the ongoing contributions of potential experts remains to be determined. Quantifying the significance of the relationship between extrinsic motivations and the continued contributions of potential experts enables us to reveal how extrinsic motivations affect potential experts' continuous contributions.

RQ2: To What Extent Does the Status of Potential Experts Moderate the Link between Their Extrinsic Motivations and Their Continued Contributions within Developer Q&A Communities?

After completing the study of RQ1, we can obtain knowledge about the influence of extrinsic motivation on the sustained contribution of potential experts. However, the effect is not set in stone. Previous research has shown that developer status changes affect their perception of community and incentives and, thus, their behavior [13, 14]. Quantifying the significance of the moderation of status on the influence of extrinsic motivations enables us to find how status affects the influence of extrinsic motivations on potential experts' continuous contributions.

RQ3: How Do the Rules of the Impact of Extrinsic Motivations on Continuous Contributions Differ between Potential Experts and Active Developers in Developer Q&A Communities?

After completing the study of RQ1 and RQ2, we have identified the rules of the influence of extrinsic motivations on potential experts. It still needs to be determined the difference in the rules of their impact on the continued contributions of potential experts and active developers. By doing so, we can reveal the difference in the rules of the impact of extrinsic motivations on the sustained contributions of potential experts and active developers to provide insights for designing incentive mechanisms to cultivate more experts.

Our work has the following contributions:

(1) We adopt the SDT to provide a hypothetical motivational impact model to describe and a multifactor assessment model to evaluate the relationship between their motivations and contributions.
(2) We provide a status-based timeline partitioning method that can overcome the defect of not accurately measuring developers' contributions at a certain status in previous research.
(3) Our study enriches the research on the rules of the influence of extrinsic motivations on developers' continued contribution to developer Q&A communities. For example, reputation affects the two types of developers' continuous contributions differently.
(4) Our findings provide strategies for community managers to cultivate more experts. On the one hand, the difference between the two types of developers can help managers identify potential experts to direct them to address challenging software development questions in the communities. On the other hand, the difference found can provide insights to fine-tune incentives to cultivate experts.

In the following sections, we introduce this study's preliminary in Section 2. Then, we describe our methodology in Section 3. After that, we present our results in Section 4. Finally, we discuss the results, implications, and limitations in Section 5 and conclude in Section 6.

2. Preliminary

This section introduces our research context, the SO community, the SDT theory for analyzing potential expert motivation, and the reported SO developer extrinsic motivations.

2.1. Research Context. Our choice of SO as the research context is justified by its standing as one of the most successful developer Q&A communities, boasting millions of developers, including a substantial number of experts. The community employs incentive mechanisms, such as reputation, status hierarchy, and badges, influencing potential experts' contributions. While the section comprehensively outlines these mechanisms, there exists a specific research gap concerning the discussion of our innovative status-based timeline partitioning method, which is pivotal in our methodology.

The selection of SO as the research context is underpinned by the effectiveness and significance of its incentive mechanisms. The rationale is threefold.

(1) Community Success: SO stands as one of the most successful developer Q&A communities globally, serving a vast developer base, including thousands of experts. The proven success of SO attests to the efficacy of its incentive mechanisms in cultivating a thriving and collaborative community.
(2) Motivation Impact: the intricate interplay between reputation, status, and badges significantly influences developers' motivations. These mechanisms have been finely tuned to elicit sustained contributions, making SO an ideal case for studying the impact of extrinsic motivations on potential experts' behavior.
(3) Data Availability: SO provides extensive and downloadable datasets containing rich behavioral information. This abundance of data facilitates a comprehensive study of developer motivations, allowing for a nuanced analysis of how incentive mechanisms shape continuous contributions.

What's more, we collected potential experts' reputations and acquisition dates from 10 versions of SO datasets from the Brentozar website from 2016 to 2019. This historical dataset offers a comprehensive view of developers' behaviors, including contributions, reputations, and status changes. To address potential concerns about the dataset's timeliness, we have developed a strategic backup plan as follows:

(1) Primary Data Source Justification. SO's incentive mechanisms have remained unchanged since March 19, 2010. Leveraging this stable period allows us to capture and analyze the extrinsic motivations that have consistently influenced potential experts' continuous contributions over a significant timeframe.

(2) Real-Time Data Limitations Acknowledgment. Recognizing the challenges associated with obtaining real-time data directly from the SO community, we proactively acknowledge the limitations. This acknowledgment forms the basis for our backup plan, ensuring that potential constraints do not compromise the study's integrity.

(3) *Expert Sampling*. To ensure the relevance of our study, we carefully selected experts from the historical dataset. By identifying developers with a reputation of 20,000 or more and registering after January 1, 2016, we established a representative sample of potential experts who actively contributed to the community.

(4) Monitoring Dataset Updates. While our primary reliance is on the historical dataset, we will continually monitor for updates to the SO dataset. Any new releases or relevant datasets will be assessed for potential integration to enhance the study's comprehensiveness.

In essence, the incentive mechanisms in SO form a crucial backdrop for investigating the motivational impact on potential experts' sustained contributions, ensuring a robust and insightful examination of extrinsic motivations within the developer community.

Table 1: Primary extrinsic motivations for potential experts.

Regulation style	Motivations	Related literature
External regulation	Badge	[8, 23]
Introjected regulation	Reputation	[8, 23–25]
	Privilege (status)	[8, 24, 26]
Identified regulation	Learning	[8, 23, 25]
Integrated regulation	Reciprocity	[8, 27, 28]

2.2. The SDT Theory. The SDT can serve as a plausible theoretical framework for revealing the rules of the influence of the motivations of potential experts. First, certain features of these communities, such as allowing voluntary posting and evaluation, correspond to the fundamental needs defined by SDT: autonomy, competence, and relatedness [6]. Second, by differentiating motivations, the SDT allows us to quantify and analyze the motivations affecting potential experts' continuous contributions, considering their needs. Third, the SDT defines a motivation continuum, which facilitates exploring the role of status in the relationship between motivations and potential experts' continuous contributions.

In detail, the SDT divides extrinsic motivation into external regulation, introjected regulation, identified regulation, and integrated regulation [17, 18]. External regulation involves external demands or tangible rewards, such as monetary rewards [19]. Introjected regulation applies intangible rewards or punishments, such as gaining praise or avoiding guilt [20]. Identified regulation reflects a conscious valuing of behavioral goals and regulation, while integrated regulation is when an individual identifies sufficiently with the value of an activity that it becomes a habitual part of the self [21].

While the SDT is adeptly introduced, a research gap is discerned in the need for a more explicit linkage between the SDT and our proposed methodology. Specifically, there is a requirement for a deeper exploration of how the motivation continuum, as defined by SDT, is applied in our study, especially in the context of the status-based timeline partitioning method.

2.3. SO Developers' Extrinsic Motivations. Lu et al. [22] have reported that the primary extrinsic motivations for SO developers to participate in community contributions were badge, reputation, learning, privilege, and reciprocity. As shown in Table 1, these motivations belong to several regulation styles based on SDT and have been examined in several studies.

(1) Badge. Despite the digital nature, badges adopt a tangible form (e.g., shape and color) to summarize the owners' skills and accomplishments. Hence, the badge reward is generally considered an external regulation [23].
(2) Reputation. A developer's reputation is generally measured by virtual points from peers' feedback, such as ratings and reviews. Due to its intangible nature, reputation falls under introjected regulation [29].

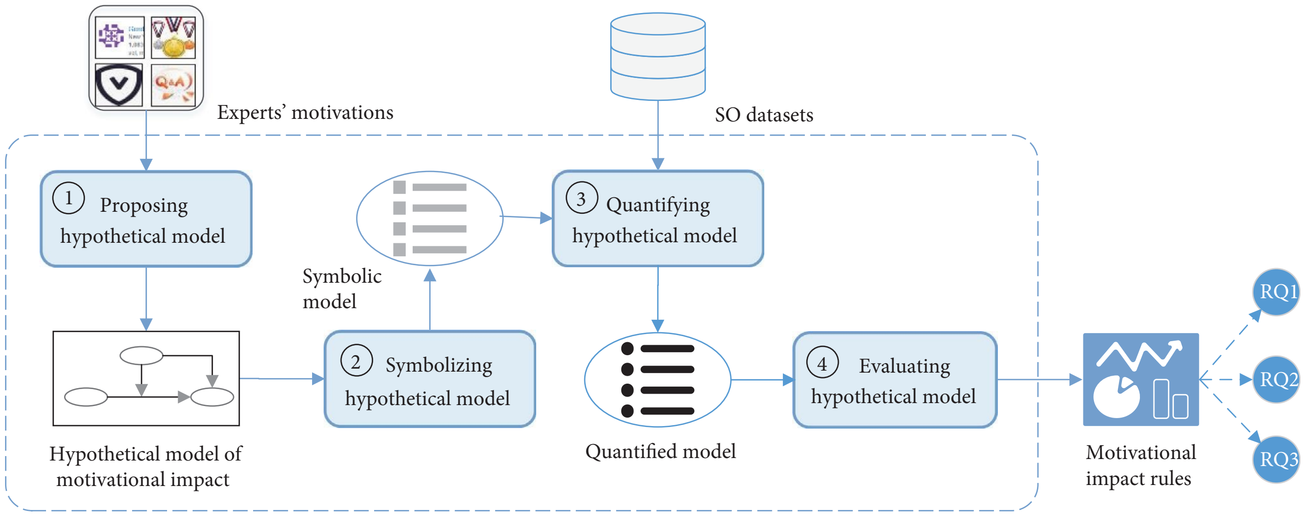

Figure 1: The flowchart of the proposed method.

(3) Privilege. SO grants developers a status when they reach a certain threshold of accumulated reputation points. This status corresponds to a particular privilege. Therefore, this study uses status to express the privilege motivation. Because status and privilege are associated with respect and admiration [30], they can be regarded as an introjected regulation.

(4) Learning. SO provides a knowledge-sharing platform for developers to improve their professional skills by answering others' questions or viewing peers' posts [8]. SO developers can acquire knowledge or information to solve their software development issues and develop their professional skills [31]. Learning on the developers' part reflects a conscious valuing of their goals and regulation of their knowledge-seeking behavior. For that reason, learning is generally placed under identified regulation.

(5) Reciprocity. Reciprocity refers to developers' expectation that their contributions should be repaid somehow. Developers motivated by reciprocity believe their communities are a reciprocal system. They desire to return the favor received and expect returns for their contributions [32]. Reciprocity means that developers fully agree with the idea of the SO community and make it their behavior. Therefore, it belongs to integrated regulation.

The work [22] explored the influence of the above motivations on developers' contributions. However, it did not distinguish the two types of developers and reveal the rules of influence of the motivations on the contribution behavior of potential experts.

The motivations of SO developers are well-documented; however, a research gap emerges in the omission of a clear distinction between different types of developers, particularly potential experts. Additionally, there is a need to uncover the rules governing the influence of motivations on the contribution behavior of potential experts, a facet not adequately addressed in the existing literature.

Table 2: Reputation update rules in SO.

Rule	Action	Reputation change
1	Question is upvoted	+10 to owner
2	Question is downvoted	−2 to owner
3	Answer is upvoted	+10 to owner
4	Answer is downvoted	−2 to owner
5	Downvote an answer	−1 to voter

3. Methodology

To address the above challenge, we proposed a four-step method. As shown in Figure 1, we first propose a hypothetical motivational impact model to assume the effects of the five motivations. Then, we symbolize the elements of the model to represent the influence factors of the model. After that, we consider some particular SO developers as potential experts and develop a status-based timeline partitioning method to quantify the model. Finally, we employ regression analysis to evaluate the model to reveal the rules of the influence of extrinsic motivations on potential experts' continuous contributions and to answer RQ1–RQ3.

3.1. Incentive Mechanism. To comprehensively explore the motivational dynamics within the SO community, it is imperative to delineate the incentive mechanisms employed to motivate developers. The SO community utilizes a multifaceted incentive structure, consisting of reputation [8, 13], status hierarchy [33, 34], and badges [29, 35, 36].

3.1.1. Reputation Mechanism. The SO community employs incentive mechanisms to encourage its developers to continue contributing. First, SO uses a reputation mechanism to motivate developers to participate in the community's activities, including viewing, creating, and voting on posts (i.e., questions and answers). Reputation is a virtual reward in the form of points provided by the community. Developers' reputations come from others' positive feedback. Table 2 describes

Table 3: The status hierarchy system of SO.

Status	Reputation	Privilege
22	25,000	Access to site analytics
21	20,000	Trusted user, delete, and undelete posts
20	15,000	Protect questions
19	10,000	Access to moderator tools
18	5,000	Approve tag wiki edits
17	3,000	Cast close and reopen votes
16	2,500	Create tag synonyms
15	2,000	Edit questions and answers
14	1,500	Create tags
13	1,000	Established user; create gallery chat rooms
12	500	Access review queues
11	250	View close votes
10	200	Reduce ads
9	125	Vote down
8	100	Edit community wiki; create chat rooms
7	75	Set bounties
6	50	Comment everywhere
5	20	Talk in chat
4	15	Flag posts; vote up
3	10	Remove new user restrictions; create wiki posts
2	5	Participate in meta
1	1	Create posts

the reputation update rules in SO. For example, when a post is voted up, the owner receives ten reputation points.

3.1.2. Status Hierarchy Mechanism. SO employs a status hierarchy mechanism consisting of 22 levels. As shown in Table 3, a status may be awarded to developers when their reputations reach a certain threshold. For example, when developers earn 20,000 reputation points, they are awarded the 21st status. Meanwhile, the community grants them the privilege to delete and undelete posts.

3.1.3. Badge Mechanism. SO adopts a badge mechanism to motivate its contributors. A badge is a virtual medal that rewards developers for making especially helpful contributions. For example, if a question scores 25 points or more, the owner receives a "Good Question" badge. Please refer to the SO website for details about its incentive mechanism (https://www.stackoverflow.com/help).

3.2. Proposing Hypothetical Model. Following the flowchart of the proposed method, we proposed a hypothetical motivational impact model for potential experts using SDT and the findings on the impact of extrinsic motivations on active developers (see Figure 2). The model includes the hypotheses on the incentive of extrinsic motivations and the hypotheses on the moderation of status. The former assumes the impact of extrinsic motivations on the sustained contribution of potential experts (RQ1), while the latter assumes how status changes these impacts (RQ2).

3.2.1. Hypotheses on Incentive of Extrinsic Motivations. As mentioned earlier, the badge is an external motivation of potential experts. Obtaining badges can meet developers' psychological needs for competence and relatedness by SDT [35]. First, obtaining badges shows that a developer can help solve others' problems. As such, badges obtained enhance developers' sense of self-efficacy [37]. Second, obtaining badges makes developers more willing to interact with peers through various tasks, which helps promote their experience of relatedness. All of these can increase the amount of subsequent contribution behavior [7]. Thus, we hypothesize that:

H1. Badge facilitates potential experts' continuous contributions to developer Q&A communities.

Like the badge, gaining reputations makes developers feel competitive to meet their psychological needs for competence. Thus, the reputation motivation encourages developers to contribute continuously [29, 35, 36]. Accordingly, we suggest the following hypothesis:

H2. Reputation facilitates potential experts' continuous contributions to developer Q&A communities.

The desire for status is a fundamental motivation of humans [30]. Higher status can lead to more benefits for developers, such as better access to scarce resources and specific privileges [8]. According to SDT, higher status can give developers a sense of dominance or control over others. Pursuing status may direct developers to make more contributions [13]. Accordingly, we propose the following hypothesis:

H3. Status facilitates potential experts' continuous contributions to developer Q&A communities.

Developers motivated by the learning factor believe their knowledge and abilities may benefit from contributing [33, 34]. However, as their stocks of skill sets continue to grow, developers tend to play an opinion leader and not accept others' ideas easily because that reveals their lack of competitiveness [13]. Ultimately, learning diminishes developers' continued contribution [13]. Hence, we hypothesize that:

H4. Learning reduces potential experts' continuous contributions to developer Q&A communities.

Reciprocity refers to the expectation that a developer who has received help must repay the favor [8]. Motivated by reciprocity, developers who have received help from others should help others [38]. Based on the SDT, such interactions between developers meet their needs for relatedness. Previous research found that reciprocity positively affects developers' contributions to the SO community [27, 28, 39, 40]. Based on these findings, we propose the following hypothesis:

H5. Reciprocity facilitates potential experts' continuous contributions to developer Q&A communities.

3.2.2. Hypotheses on Moderation of Status. Developers of lower status tend to strive for badges and reputation points to reach higher status for more benefits [11]. However, they tend to care less about extrinsic incentives such as reputation after earning rewards and reaching a certain status than before [10]. According to SDT, people's inner needs determine their motivational strength [41]. Therefore, we assume

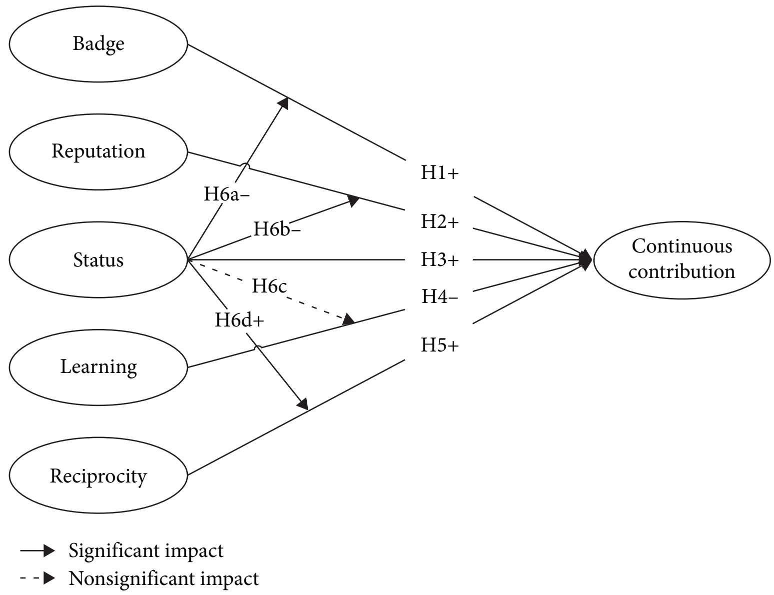

Figure 2: Hypothetical motivational impact model. The symbols + and − indicate a positive or negative impact, respectively.

that badge and reputation exert a weaker impact on potential experts' continuous contributions when they are at a higher status than at a lower one.

Researchers have found that the impact of status on learning is twofold. On the one hand, the higher the status of developers, the more they want to develop their skills to stay at the cutting edge of technology. As a result, they are more likely to acquire knowledge and increase productivity through learning [31]. On the other hand, when developers are of relatively high status, they tend to exert influence over the opinions and decisions of their peers. Thus, they are less likely to be influenced by others. Learning means they must also acquire knowledge from their peers, which may expose their shortcomings [13]. Therefore, status's effect on developers' learning is insignificant [13].

We have yet to find studies reporting the impact of status on the influence of reciprocity. According to SDT, when developers are of higher status, they behave in search of pleasure or satisfaction and to obtain the benefit of the activity itself [32]. Reciprocity could improve personal importance, value, and a sense of community [42]. Thus, reciprocity may impact developers' contributions more when they are at a higher status than a lower one.

Based on the analysis above, we propose the following four hypotheses:

(1) H6a. Status weakens the impact of a badge on potential experts' continuous contributions.

(2) H6b. Status weakens the impact of reputation on potential experts' continuous contributions.

(3) H6c. Status does not significantly affect the impact of learning on potential experts' continuous contributions.

(4) H6d. Status strengthens the impact of reciprocity on potential experts' continuous contributions.

Table 4: Description of measure variables.

Type	Name	Item
Dependent variable	Developer contribution	*pt*
Independent variable	Badge	*b*
	Reputation	*r*
	Learning	*l*
	Reciprocity	*rc*
Control variable	Day	*d*
	Personal page	*u*
Moderator variable	Status	*st*

3.3. Symbolizing Hypothetical Model. This study assumes that motivations affect potential experts' contributions to the community. Therefore, we considered potential experts' contributions and motivations as dependent and independent variables, respectively. Because of the moderation of status, we considered potential experts' status as a moderator variable.

In addition, this work adopted two control variables that have been reported to affect potential experts' contributions to online communities. The first variable, a developer's tenure, indicates their loyalty to the community, which may influence their future behavior [43]. Therefore, we took into account the tenure of potential experts. The second variable is the potential expert's personal page, which reflects their willingness to interact with others [44].

As shown in Table 4, we used a dependent variable, *pt*, to indicate their contributions. For independent variables, we used the variables *b*, *r*, *l*, and *rc* to indicate the strength of the four motivations of potential experts, respectively. For the moderator variable, we used the variable *st* to indicate the strength of motivation for status. In addition, we used a variable *d* and a dummy variable *u* to represent potential experts' tenure and whether they provide links to their personal pages.

3.4. Quantifying Hypothetical Model. In order to quantify the hypothetical motivational impact model, we first selected SO developers whose reputations increased from 1 to 20,000 between January 1, 2016, and September 1, 2019, as potential experts. Second, we developed a status-based timeline partitioning method to determine the statistical intervals of model variables. Finally, we employed some means to measure these variables to quantify the hypothesis model.

3.4.1. Potential Expert Collection. Accurately identifying potential experts among SO developers is a prerequisite for this study. Movshovitz-Attias et al. [15] considered developers who can obtain reputation points greater than or equal to 2,400 as potential experts. Drawing on their idea, we used the reputation of developers as a measure of their expertise. Developers with more than or equal to 20,000 points are considered "trusted users" in SO and are generally distinguished from normal developers as highly skilled developers [45]. Therefore, we defined these developers as experts and regarded them as potential experts before they became experts.

To obtain potential experts, we downloaded the SO dataset as of September 1, 2019, provided by the Brentozar website (https://www.brentozar.com/archive/2015/10/how-to-download-the-stack-overflow-database-via-bittorrent/). The dataset contains 10,932,295 developers and their behavior information. We ran Structured Query Language (SQL) on the dataset to examine all SO developers with a reputation of 20,000 or more as of September 1, 2019. As a result, 7,049 developers were chosen as experts. Moreover, we applied SQL statements to select the developers among the experts who registered after January 1, 2016. The 120 experts obtained were collected as the samples of this study. SO's incentive mechanisms have remained unchanged since March 19, 2010. Thus, these developers are suitable as samples to explore the extrinsic motivations of the community's potential experts and help us measure the influence of extrinsic motivations on their continuous contributions.

3.4.2. Status-Based Timeline Division. Previous studies measure the extrinsic motivations of developers according to their behavior information in an artificial timeline division period, such as 30 days [13, 14]. Developers' statuses change continuously in each artificial timeline division period. Thus, the approach is challenging to accurately count developers' behavior information at a certain status. This may lead to bias in exploring the influence of status on developer contribution.

We developed a status-based timeline partitioning method to improve developers' behavior information count accuracy at each status. The method counts the behavior information of potential experts based on the dates between two adjacent statuses. However, the SO community does not provide the date on which a certain status and its corresponding reputation are acquired. To estimate potential experts' each status acquisition date, we collected their multiple reputations, obtained dates, and used the linear interpolation method [46].

Table 5: Description of the SO datasets.

Version	Duration
10	From September 1, 2008 to September 1, 2019.
9	From September 1, 2008 to June 1, 2019.
8	From September 1, 2008 to December 2, 2018.
7	From September 1, 2008 to September 2, 2018.
6	From September 1, 2008 to June 3, 2018.
5	From September 1, 2008 to December 3, 2017.
4	From September 1, 2008 to August 27, 2017.
3	From September 1, 2008 to June 11, 2017.
2	From September 1, 2008 to January 1, 2017.
1	From September 1, 2008 to March 6, 2016.

(1) Reputation Date Collection. As shown in Table 5, we collected potential experts' reputations and acquisition dates from ten versions of SO datasets from the Brentozar website from 2016 to 2019. Each data set contains an accumulated reputation and acquisition date of developers. From the ten datasets, we obtained 10 accumulated reputations and their acquisition dates of each potential expert.

(2) Status Date Estimation. Figure 3 depicts the relationship between a potential expert's multiple cumulative reputation points and their acquisition dates from the downloaded datasets. Here, j indicates the version number of a SO dataset. $r_{i,j}$ and $d_{i,j}$ are the accumulative points and the acquisition date of the ith potential expert in the jth dataset, respectively. r_s represents the corresponding reputation of the sth status according to the incentive mechanism of SO. The estimated $dt_{i,s}$ represents the date on which the reputation of the sth status of the ith potential expert is obtained. According to the rules of SO, the corresponding reputation of the first status is one, and its acquisition date is a developer's registration date.

From the relationship in Figure 3, we can use the linear interpolation method to estimate the acquisition dates of potential experts' statuses, as described by Equation (1).

$$dt_{i,s} = dt_{i,j-1} + \frac{r_s - r_{i,j-1}}{r_{i,j} - r_{i,j-1}} \times \left(d_{i,j} - d_{i,j-1}\right). \tag{1}$$

3.4.3. Hypothetical Model Quantification. After obtaining status dates, we collected information on potential experts' behavior information based on the status period from the 10th dataset in Table 5 to quantify the hypothetical model. Table 6 presents the quantification of the model variables.

(1) Contribution pt. Developers may contribute to the community in multiple forms, such as asking questions, providing answers, and editing or commenting on existing questions or answers. This work focused only on the two basic contribution activities: asking or answering questions. Both are the most vital activities for the success of any Q&A community. Accordingly, the variable pt was measured by the average number of questions and answers created daily by potential experts of different statuses when we investigated their ongoing contributions from the 2nd to 21st status.

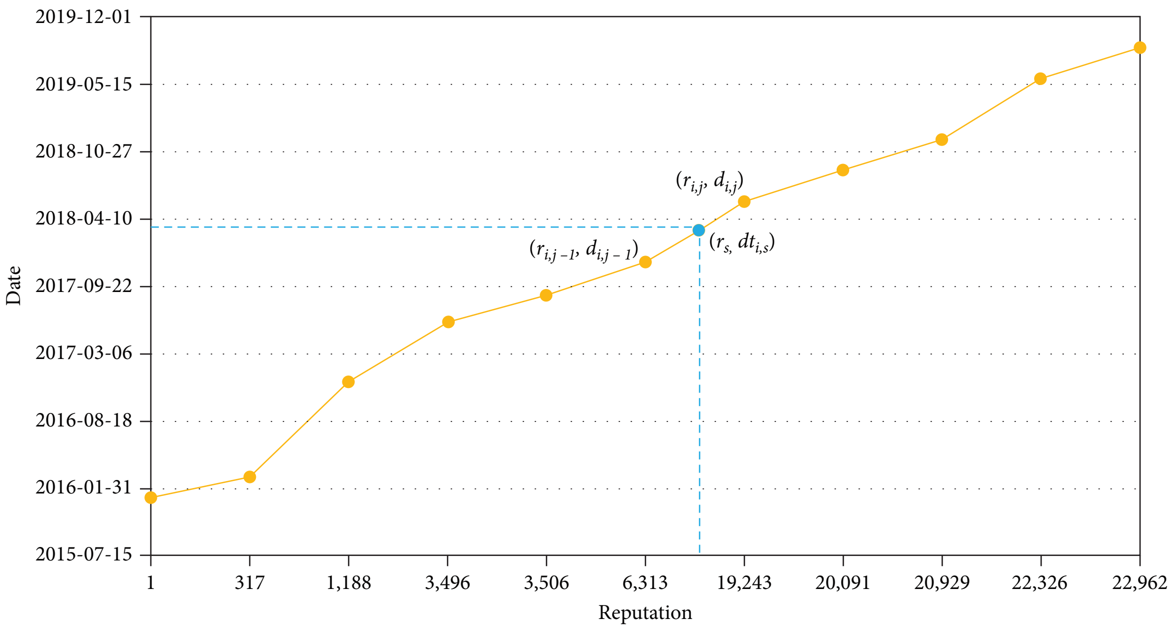

Figure 3: The relationship between a potential expert's reputations and their acquisition dates. The abscissa represents the potential expert's reputations r in the downloaded datasets, while the ordinate represents their acquisition dates d.

Table 6: Quantification of model variables.

Name	Item	Quantification
Contribution	$pt_{i,s}$	Average daily posts created by the ith potential expert at the sth status
Badge	$b_{i,s}$	Average daily badges earned by the ith potential expert at the sth status
Reputation	$r_{i,s}$	Average daily points gained by the ith potential expert at the sth status
Learning	$l_{i,s}$	Average daily upvotes of the ith potential expert at the sth status
Reciprocity	$rc_{i,s}$	Average daily answers received of the ith potential expert at the sth status
Day	d_i	Length of use of the ith potential expert since registration (in days)
Personal page	u_i	A dummy variable for the personal page of the ith potential expert
Status	$st_{i,s}$	Inverse number of days to obtain the sth status of the ith potential expert

(2) Badge b. There are three levels (bronze, silver, and golden) and multiple types (e.g., question badge, answer badge) of badges in SO. A single badge only motivates developers to contribute as they are about to earn it [47]. Therefore, this work does not distinguish between badge levels and types and only focuses on the combined impact of badges on developers' continuous contributions. The community provides statistics for developers' badges displayed on their profiles. In this work, we adopted the average daily badges of potential experts to measure the strength of their badge motivation b at a status.

(3) Reputation r. Like badges, developers' reputation points are displayed on their profiles, motivating them to contribute. In this work, we employed the average earned reputation points per post of potential experts to measure the strength of their reputation motivation r at a status.

(4) Learning l. The primary goal of SO is to provide developers with solutions and ideas regarding their technical questions. Developers can obtain knowledge and information by viewing peers' questions, answers, and comments. When they recognize the posts viewed, they may upvote the posts. The number of upvotes reflects developers' desire to acquire knowledge. Thus, we used potential experts' daily upvotes to measure the strength of their learning motivation l at a status.

(5) Reciprocity rc. Potential experts generally desire to return the favor to the community for the answers to their questions received from peers. Potential experts may answer others' questions to return the favor, which can be considered a behavior driven by reciprocity. Thus, we used potential experts' daily answers received to measure the strength of motivation for reciprocity rc at a status.

(6) Status st. Status is the moderator variable in our analysis, which reflects potential experts' relative positions in the status hierarchy of the community. The number of statuses belongs from 1 to 20. We used the variable st to indicate the strength of motivation for status. The motivation level of a potential expert at a status can be measured by the inverse number of days to obtain the status.

(7) Day d and personal page u. This work employs the length of use of the ith potential expert since registration (in days) to represent the expert's tenure d_i. In addition, we used

Table 7: Descriptive statistics of model variables.

Variable	Max	Min	Mean	Std. dev.
pt	46.753	0.070	0.996	1.992
b	40.377	0.058	0.812	1.717
r	357.143	0.000	27.077	35.945
l	301.950	0.000	12.621	27.399
rc	2.125	0.003	0.044	0.091
st	1	0.001	0.109	0.209
d	1,152	1	133.067	194.314
u	1	0	0.839	0.368

a dummy variable u_i to represent whether they provide links to their personal pages.

Table 7 presents the descriptive statistics of the variables. We centralized the *b*, *r*, *st*, *l*, and *rc* variables to simplify the calculation. We provided details about the measurement items on the GitHub site.

3.5. Evaluating Hypothetical Model. After quantifying the hypothetical model, we first employed regression analysis to construct multifactor assessment models to obtain the findings of RQ1 and RQ2. We then compared these findings with the impact of extrinsic motivations on active developers to answer RQ3.

3.5.1. Evaluation Method. Our work employed regression analysis to analyze the significance of the relationship between extrinsic motivations and potential experts' continuous contributions. This study's dependent variable is only the potential expert contribution *pt*, and all independent variables can be measured. Therefore, we used a relatively simple but adequate regression analysis and did not adopt the more powerful but complex path analysis and structural equation analysis [48].

Considering there may be multicollinearity between independent variables, we adopted the ridge regression analysis. The regression is a variable approach to estimating the coefficients of multiple-regression equations, which is particularly suitable in scenarios with multicollinearity among the variables [49]. We can estimate the relationship between the dependent and independent variables using the equations' coefficients and their significance.

3.5.2. Multifactor Assessment Model. Using the measurement items and ridge regression analysis, we constructed three ridge regression models to examine the incentive effects of extrinsic motivations and the moderating effect of status, divided into the incentive and moderation models.

(1) Incentive Model. To test the proposed hypotheses H1–H5, we developed incentive models M1 and M2. The developed M1 described in Equation (2) reflects the incentive effects of extrinsic motivations at the *s*th status on the contribution at the *s* + 1th status.

$$\begin{aligned} M1: pt_{i,s+1} = \; & c_{i,s} + \alpha_1 \times b_{i,s} + \alpha_2 \times r_{i,s} + \alpha_3 \times l_{i,s} + \alpha_4 \times rc_{i,s} \\ & + \alpha_5 \times st_{i,s} + \varepsilon_{i,s}, \end{aligned} \tag{2}$$

where $i \in [1, n]$ indexes the potential expert, and $s \in [1, 20]$ indexes the status. α is the parameter to be estimated. $pt_{i,s+1}$ is the dependent variable presenting the *i*th potential expert's contributions to SO at the *s* + 1th status. $b_{i,s}$, $r_{i,s}$, $l_{i,s}$, $rc_{i,s}$, and $st_{i,s}$ are the independent variables, indicating the strength of the *i*th potential expert's various motivations at the *s*th status. In addition, $c_{i,s}$ and $\varepsilon_{i,s}$ are the model's constant and error terms, respectively.

The developed M2 described in Equation (3) reflects control variables' influence on extrinsic motivations' incentive effects.

$$\begin{aligned} M2: pt_{i,s+1} = \; & c_{i,s} + \alpha_1 \times b_{i,s} + \alpha_2 \times r_{i,s} + \alpha_3 \times l_{i,s} + \alpha_4 \times rc_{i,s} \\ & + \alpha_5 \times st_{i,s} +, \; \beta_1 \times d_i + \beta_2 \times u_i + \varepsilon_{i,s}, \end{aligned} \tag{3}$$

where d_i and u_i are the control variables that represent whether the *i*th potential expert has a personal page and his/her registration days, respectively. β is the parameter to be estimated.

(2) Moderation Model. The developed moderation model M3 is described in Equation (4). The model was developed by adding four interaction items to the model M2.

$$\begin{aligned} M3: pt_{i,s+1} = \; & c_{i,s} + \alpha_1 \times b_{i,s} + \alpha_2 \times r_{i,s} + \alpha_3 \times l_{i,s} + \alpha_4 \times rc_{i,s} \\ & + \alpha_5 \times st_{i,s} + \beta_1 \times d_i +, \; \beta_2 \times u_i + \gamma_1 \times st_{i,s} \times b_{i,s} \\ & + \gamma_2 \times st_{i,s} \times r_{i,s} + \gamma_3 \times st_{i,s} \times l_{i,s} \\ & +, \; \gamma_4 \times st_{i,s} \times rc_{i,s} + \varepsilon_{i,s}, \end{aligned} \tag{4}$$

where $st_{i,s} \times b_{i,s}$, $st_{i,s} \times r_{i,s}$, $st_{i,s} \times l_{i,s}$, and $st_{i,s} \times rc_{i,s}$ are interaction items adopted to test the moderation of status on the impact of motivations on potential experts' continuous contributions.

4. Results

We set the ridge coefficient *k* in the three models to 0.15 according to the ridge trace map obtained. We ran our assessment models on the dataset collected and presented the results for our research questions.

4.1. RQ1: What is the Relationship between Extrinsic Motivations and the Sustained Contribution of Potential Experts in Developer Q&A Communities? Table 8 shows that the regression coefficients of the variables in M1 and M2 remain unchanged in terms of signs and significances, indicating the good stability of the two models. Furthermore, the significant *F*-values ($F > 269.287$ and $p < 0.01$) suggest that there is a regression relationship between the dependent variable and the independent variables, although the fitting performance is mediocre ($R^2 > 0.436$).

In detail, badge and reciprocity have a positive effect ($\alpha = 0.293$, $p < 0.01$ and $\alpha = 0.305$, $p < 0.01$), while reputation and status negatively impact on potential experts' continuous contributions to SO ($\alpha = -0.015$, $p < 0.05$ and $\alpha = -0.007$, $p < 0.05$). However, the learning factor shows no significant effect in our model. This evidence supports our hypotheses

Table 8: Parameter estimation of the incentive models ($N=120$).

Variables	M1	M2
b	0.296^{***} (35.459)	0.293^{***} (35.091)
r	-0.014^{**} (−2.344)	-0.015^{**} (−2.545)
l	−0.002 (−0.267)	−0.001 (−0.181)
rc	0.311^{***} (37.493)	0.305^{***} (36.787)
st	-0.011^{***} (−3.926)	-0.007^{**} (−2.507)
d	—	0.018^{***} (5.233)
u	—	−0.001 (−0.652)
Constant	0.011	0.009
R^2	0.436	0.441
F	369.409^{***}	269.287^{***}

Note: The t-values are in parentheses. The larger the absolute t-values, the more significant the influence of motivations. In addition, $^{*}p<0.1$, $^{**}p<0.05$, and $^{***}p<0.01$.

Table 9: Parameter estimation of the moderation model ($N=120$).

Variables	M2	M3
b	0.293^{***} (35.091)	0.292^{***} (34.361)
r	-0.015^{**} (−2.545)	-0.015^{**} (−2.388)
l	−0.001 (−0.181)	−0.008 (−1.044)
rc	0.305^{***} (36.787)	0.303^{***} (36.025)
st	-0.007^{**} (−2.507)	-0.009^{***} (−2.919)
d	0.018^{***} (5.233)	0.021^{***} (5.684)
u	−0.001 (−0.652)	0.001 (−0.657)
$b \times st$	—	0.32 (0.742)
$r \times st$	—	0.058 (0.421)
$l \times st$	—	0.044 (0.635)
$rc \times st$	—	0.69^{*} (1.607)
Constant	0.009	0.008
R^2	0.441	0.442
F	269.287^{***}	171.71^{***}

Note: The t-values are in parentheses. $^{*}p<0.1$, $^{**}p<0.05$, and $^{***}p<0.01$. M2 is added for comparison.

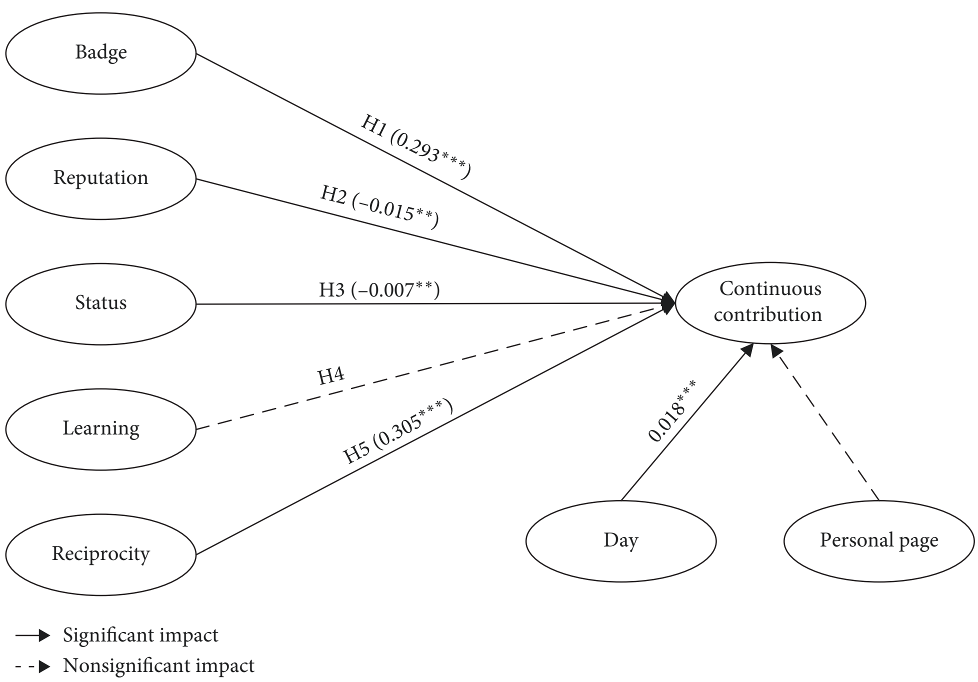

Figure 4: Incentive of potential experts' extrinsic motivations.

of H1 and H4 but fails to support those of H2, H3, and H5 (see Figure 4).

Regarding the control variables in the model M2, potential experts' tenures d positively affect their continuous contributions ($\beta=0.018$, $p<0.01$), while the personal page u has no significant impact.

> *Finding 1: Badge and reciprocity facilitate potential experts' continuous contributions. Reputation and status reduce potential experts' ongoing contributions. Additionally, learning does not significantly affect potential experts' continued contributions.*

4.2. RQ2: To What Extent Does the Status of Potential Experts Moderate the Link between Their Extrinsic Motivations and Their Continued Contributions within Developer Q&A Communities? M3 in Table 9 presents the moderation of status. The regression coefficients of the variables remain unchanged in terms of signs and significances, indicating the excellent stability of the three regression models. Furthermore, the significant F-value ($F=171.71$ and $p<0.01$) of M3 suggests that there is a good regression relationship between its dependent variable and independent variables, although its simulation capability ($R^2=0.442$) is mediocre.

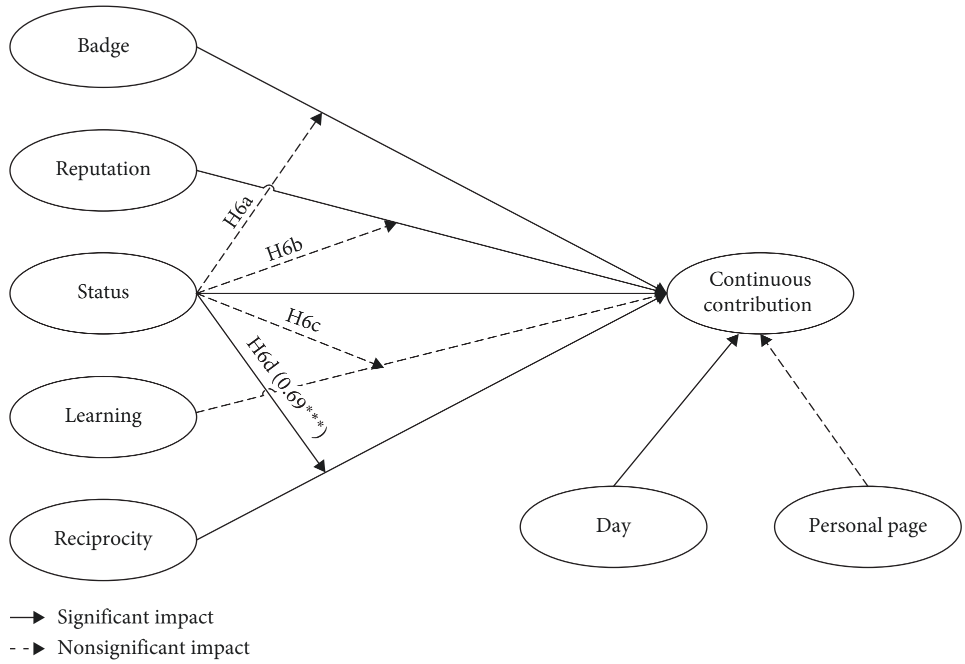

Figure 5: Moderation of potential experts' status.

As shown in Table 9, status only strengthens the impact of reciprocity ($\gamma = 0.690$, $p < 0.1$) on potential experts' continuous contributions, while it does not significantly affect the impact of the other three factors. Hence, H6c and H6d are supported, but H6a and H6b are not (see Figure 5).

Finding 2: Status only strengthens the promotion of reciprocity on potential experts' continuous contributions while not significantly affecting the impact of badge, reputation, and learning on potential experts' continuous contributions.

4.3. RQ3: How Do the Rules of the Impact of Extrinsic Motivations on Continuous Contributions Differ between Potential Experts and Active Developers in Developer Q&A Communities? We have presented the influence of extrinsic motivations on active developers described in Section 3.1. We compared them with the findings of RQ1 and RQ2 to answer RQ3.

Table 10 shows differences between the influences of four extrinsic motivations on the contributions of both types of developers. Reputation and status reduce potential experts' continuous contributions but positively affect those of active developers. Learning does not significantly affect potential experts' continuous contributions while negatively affecting active developers.

Additionally, status only strengthens the impact of reciprocity on potential experts' contributions. It does not significantly affect the impact of badge, reputation, and learning on potential experts' contributions. For active developers, status significantly moderates the impact of badges and reputation on their contributions.

Table 10: Comparison between two types of developers.

Path	Potential experts	Active developers
Badge⟶post	+	+ [7, 9, 13]
Reputation⟶post	−	+ [9, 13, 35]
Learning⟶post	/	− [13, 33, 34]
Reciprocity⟶post	+	+ [9, 27, 28]
Status⟶post	−	+ [13]
Status⟶(badge⟶post)	/	− [13]
Status⟶(reputation⟶post)	/	− [13]
Status⟶(learning⟶post)	/	/ [13]
Status⟶(reciprocity⟶post)	+	

Note: Path $a \longrightarrow b$ represents the effect of factor a on factor b. The symbols +, −, and / indicate positive, negative, and not significant impact, respectively.

Finding 3.1: Reputation and status negatively affect potential experts' contributions but positively affect that of active developers.

Finding 3.2: Learning does not significantly affect potential experts' contributions but negatively affects active developers.

Finding 3.3: Status only has a significant moderating effect on the relationship between reciprocity and potential expert contributions. However, status significantly moderates the effect of badges and reputation on active developer contributions.

5. Discussion

This section introduces the interpretations, implications, and threats to the validity of our findings.

5.1. Interpretations. We have found differences in the impact of extrinsic motivations on the ongoing contributions of potential experts and active developers. Exploring their causes can provide some implications for researchers and practitioners.

5.1.1. Incentive of Extrinsic Motivations. Reputation negatively affects potential experts' continued contribution behavior. The result differs from the findings in that reputation positively affects active developers' continuous contributions [9, 13]. After gaining a great reputation, potential experts are less concerned with the external benefits of activities than active developers. Conversely, they pay more attention to the meaning and value of the contribution itself [10]. For example, according to our data analysis, potential experts are more likely than active developers to vote down others' posts to maintain the quality of posts, even if it costs them points. As a result, potential experts' ongoing contributions negatively correlate with their reputation. Due to the correspondence between status and reputation, their effects on developers' contributions are similar.

Learning does not significantly affect potential experts' continuous contributions. This result differs from the fact that motivation negatively affects active developers' ongoing contributions [13]. Potential experts are more willing than most active developers to improve their skills through learning. They view and vote on posts that give them information more often than active developers [50]. However, when they accumulate some knowledge and skills, they are more inclined to influence the views of other developers than to be influenced by others [13]. Thus, the dual effects may result in learning having no significant impact on the ongoing contributions of potential experts.

5.1.2. Moderation of Status. Status does not significantly affect the impact of badge and reputation on potential experts' continuous contributions, which is different from its negative moderation effect on active developers. The relationship suggests that the incentive effect of badge and reputation on the continued contribution of potential experts is not significantly enhanced or diminished by the change in their status.

In addition, status significantly strengthens the effect of reciprocity on potential experts' continuous contributions. Potential experts are willing to answer questions to return the help obtained [8]. The higher their status, the more help they received. Thus, the effect of reciprocity on their contribution is positively affected by their change in status. We did not find research on the moderation of status on the impact of reciprocity on active developers.

5.2. Implications

5.2.1. Implication for Researchers. First, we provided a status-based timeline partitioning method, as shown in Section 3.5. The approach can longitudinally explore the effects of extrinsic motivations on potential experts' continuous contributions by estimating the acquisition dates of the status of potential experts and their contributions. Compared with the artificial timeline division method [13, 14], it overcomes the defect of not accurately counting developers' contributions at a certain status and improves the model's accuracy. Therefore, our conclusion can more accurately discover the extrinsic motivations that incubate normal developers into experts.

Second, our study enriches the research on extrinsic motivations influencing developers' continued contribution to developer Q&A communities. Previous findings based on active developers may not apply to potential experts because of differences in the motivational impact difference between the two types of developers. For example, previous research has shown that reputation promotes the continued contributions of active developers [13]. However, we found that the motivation reduces potential experts' continued contributions. Additionally, status moderates the motivational effects of potential experts and active developers differently. These results provide a more comprehensive understanding and measuring of the extrinsic motivations influencing potential experts' sustained contributions to optimize incentive mechanisms to cultivate more experts.

5.2.2. Implication for Practitioners. Our findings provide strategies for developer Q&A community practitioners to cultivate more experts. On the one hand, our findings can help them identify potential experts from active developers early on. Community practitioners can identify potential experts early by taking advantage of the differences in the impact of extrinsic motivations on the two types of developers. On the other hand, our findings provide insights into design incentives to incubate more experts.

The different effects of extrinsic motivation on the two types of developers can help community practitioners develop incentive mechanisms for cultivating experts. For example, reputation and status negatively affect the continuous contribution of potential experts. Because potential experts tend to vote on peers' posts to maintain the quality of Q&A communities, managers should consider removing the penalty for voting down posts to encourage the enthusiasm of potential experts to participate.

In summary, by identifying potential experts and taking measures to encourage them to contribute, the communities have the potential to incubate more experts to sustain their prosperity.

5.3. Threats to Validity

5.3.1. Threats to Internal Validity. We are aware of two aspects for improvement in the current study. One threat is that the cutoff date for the currently tested data is September 1, 2019. We chose this date for two reasons: first, the SO community changed the conventional incentives on November 13, 2019; second, the outbreak of the COVID-19 pandemic completely changed the behavior pattern of community developers, resulting in considerable jumps in data before and during the pandemic.

The other threat is that we could not obtain the exact dates potential experts received their statuses. The SO community does not provide detailed information on when a post gains or loses its reputation after being voted. Developers may earn a considerable reputation in several days rather than constantly getting it. This irregularity makes the prediction result of Equation (1) inaccurate.

5.3.2. Threats to External Validity. The threats to external validity are related to the generalization of our findings. Our work is conducted in the SO community. In other words, our findings need to be more generalizable to other developer Q&A communities.

6. Conclusions

This study seeks to reveal the rules of the impact of extrinsic motivations on potential expert sustained contribution in developer Q&A communities. Based on the SDT theory, we developed and empirically tested hypotheses about the relationship between extrinsic motivations and sustained contribution with the hypothetical motivational impact model and the multi-factor assessment model. Our findings reveal the incentives of extrinsic motivation on potential experts, the moderation of status on these effects, and the differences in the effects of extrinsic motivations on potential experts and active developers. These findings recommend that community practitioners identify potential experts early and optimize reputation and status incentives to incubate more experts.

In future work, we plan to compare data from before and during the COVID-19 epidemic to study the impact of such an epidemic as an external factor on community activities. Additionally, we will explore how to remove and reduce bias in developer status acquisition dates, thus improving the robustness of our model.

Data Availability

The data that support the findings of this study are available from the Brent Ozar website (https://www.brentozar.com/archive/2015/10/how-to-download-the-stack-overflow-database-via-bittorrent/) and the GitHub site (https://github.com/snryou/motivation).

Conflicts of Interest

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

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