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Short Paper

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Abstract

The bounty award system has been implemented on UGC platforms to address specific issues and improve content contributions. This study aims to assess its effectiveness by examining the bounty amount and temporal scarcity. Based on the optimistic bias theory, we posit that the competition for bounty awards among users can have a positive effect, as users may overestimate their chances of winning and persist in their efforts. Additionally, we hypothesize that the amount of bounty award does not have a linear effect on the quantity and quality of user-generated content, but instead follows an inverted U-shaped relationship. Furthermore, drawing on the stuck-in-the-middle (STIM) effect, we hypothesize that temporal scarcity influences contributors' effort allocation in a U-shaped relationship. By exploring these hypotheses, we aim to advance the understanding of the underlying mechanisms of bounty awards and contribute to the development of effective peer incentive strategies.

Keywords: Bounty awards, content contribution, temporal scarcity, the STIM effect

Introduction

The knowledge-sharing platform has evolved into a vast repository of knowledge, offering users a space to discover, create, and share knowledge. As of January 2023, Wikipedia boasts close to 45 million registered users. However, only a small fraction (i.e., 130 thousand users with editorial activity within 30 days) actively contributes to the platform daily[1]. To encourage and reward the creation of high-quality content, many UGC platforms such as Wikipedia, Stack Overflow, and Quora offer various awards to their users. Previous literature has explored general incentive mechanisms on platforms, primarily focusing on reputation (Wasko and Faraj 2005), incentive hierarchies (Goes et al. 2016), and monetary rewards

[1] https://en.wikipedia.org/wiki/Wikipedia:Wikipedians#cite_note -2

(Burtch et al. 2015). While these incentives aim to motivate users to answer general questions, more than 30% of questions on Stack Overflow remain unanswered. To tackle this issue, bounty awards have been introduced. Knowledge seekers post bounty awards as an additional incentive to get their particular problems resolved. On various Q&A platforms, bounties can be awarded to existing answers (post-reward) or attached to questions to attract more and better answers in the future (pre-reward). This study, in particular, focuses on pre-reward bounties that require users to solve the problem posted by the bounty issuer within a specified timeframe. In exchange for the effort of providing answers, the knowledge seeker typically sacrifices their virtual or real currency, such as reputation points or money. Usually, bounty amounts are typically higher than rewards for more general questions to stimulate competition among participants. However, not all content producers are eligible for bounty awards. Ultimately, only one winner can claim the entire bounty award.

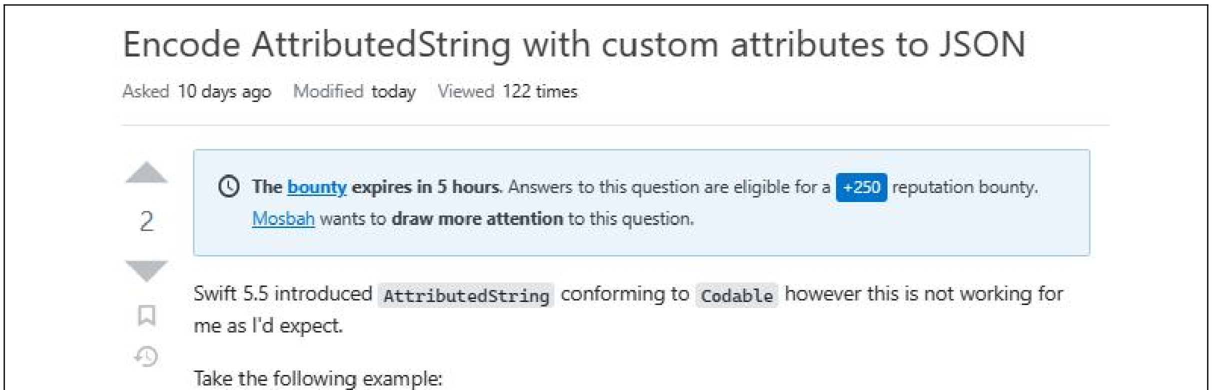

Figure 1. A Question Post on Stack Overflow with Bounty

Compared to general awards, bounty awards exhibit several notable differences. The first significant distinction is that a high bounty amount indicates a challenging question and fierce competition. Each participant will receive a prize in the general award setting if the prerequisites are satisfied. Instead, just one winner receives a bounty prize, which is often typically larger than a general award. This creates a win-or-nothing tournament. In bounty tasks, the knowledge seeker's payment, made with their own reputation, indicates the amount of effort necessary to address the issue. A higher bounty amount might signify a more challenging or complex question that takes more time and effort to answer. Some scholars (Huang et al. 2012; Terwiesch and Xu 2008) argue that as the bounty amount increases, so does the intensity of competition, and in win-or-nothing contests, participants may give up providing solutions if their efforts may not be compensated. Liu et al. (2021) propose that moderate rewards may maximize the number of participants. While increasing the bounty amount may attract more answers, it may also discourage user participation if the competition gets too intense and the chances of winning are perceived as low. The role of competition in user engagement remains a topic of debate, with conflicting research findings. For instance, a study (Shao et al., 2012) documents that high competition intensity can reduce the number of participants in crowdsourcing tasks. However, Boudreau et al. (2011) suggest that although a raise in the number of participants increases the intensity of competition in crowdsourcing contests, experts are more likely to emerge, thus having a positive impact on generating high-quality solutions. The competition inherent in bounty awards remains a subject of debate regarding its impact on user participation and solutions quality. Specifically, it is unclear whether such bounty awards attract more users' attention and stimulate high-quality production or instead suppress content contribution, undermine effort motivation, and lead to unclear outcomes.

The second one is the difference in the award issuer. The bounty award is granted by a specific peer, whereas regular rewards are granted by the platform. According to social exchange theory (Liu and Chen 2005), users on UGC platforms prefer intrinsic rewards such as recognition and encouragement from others (Gallus 2017) over extrinsic benefits while providing solutions. Moreover, positive feedback from peers has been shown to motivate new users (Burtch et al. 2022) and sustain user contributions (Jin et al. 2015; Macy 1991; Rui and Whinston 2012). The receipt of bounty awards not only satisfies extrinsic motives but also signifies approval from a particular knowledge seeker, which can operate as an internal motivator for users to engage actively and keep making efforts. We may infer from Qiao et al.'s (2020) research that one common problem with extrinsic incentives is that they can suppress altruism, which may lead to a reduction in their voluntary contributions without further incentives. Due to the bounty award's larger intrinsic motivational effect, it can therefore make up for this shortcoming.

The temporal scarcity associated with bounty awards is another unique characteristic. Platforms such as Reddit and Bountysource allow users to specify the duration of their bounty awards, often including time restrictions. Studies (Baer and Oldham 2006; Byron et al. 2010) have discussed the impact of time pressure on task performance. However, in the context of bounty incentives, particularly as the deadline approaches, temporal scarcity may induce strategic behavior among content contributors. Therefore, we consider bounty awards to function more like a bidding mechanism. The bounty provider can be considered as a bidder in accordance with the models proposed by Giebe (2014) and DiPalantino and Vojnovic (2009), and the bounty is awarded to the participant who makes the highest bid in terms of effort. In Al-Hasan et al.'s (2017) study, they observed a potential trade-off between early and late submissions and discovered that both have a better chance of succeeding than intermediate submissions. This is due to the informational spillover of early replies on late participants. According to Hofstetter et al. (2018), although the seeker favors early submissions, late submissions that mimic or duplicate them may also triumph in open competitions. The bounty question is comparable to these open crowdsourcing contests, allowing each participant to observe existing answers. Therefore, in addition to embracing the overall reward's intrinsic and extrinsic motivations, responding to the bounty question involves strategic bargaining. However, there is very little research on this behavior in the context of non-financial incentives. Hence, further discussion on the use of bounty awards as a competitive, peer-based, and strategic incentive to assist knowledge seekers in solving specific problems is warranted.

In light of this, this paper addresses three research questions. (1) To what extent are bounty awards effective at motivating greater volumes and higher quality content? (2) Does the strength of the incentive effect for content contribution increase with a higher award amount? (3) How does time scarcity impact users' performance in answering questions?

To explore these questions, we utilize the Stack Overflow data dump including all questions, answers, tags, and log of actions and their rewarded reputation points between 1/1/2017 and 12/32/2021. In this research progress, we will construct a cross-sectional dataset and a panel dataset to examine our hypotheses, respectively. The remainder of this short paper is organized as follows. In sections 2 and 3, we present a literature review on bounty awards and temporal scarcity and develop our hypotheses about how bounty awards affect the quality and quantity of content. Section 4 presents our data and context, followed by an explanation of key variables and econometric models. In the last section, we conclude with the expected contributions and discuss further work.

Literature Review

Bounty Award and Content Contribution

Previous research has demonstrated the effectiveness of both extrinsic and intrinsic motivations in encouraging user contributions (Burtch et al. 2015, 2022). Scholars have found that intrinsic motivations, such as altruism, are more effective in attracting and sustaining participant efforts compared to extrinsic motivations. Studies have explored the potential crowding-out effect of extrinsic motivations on intrinsic motivations (Qiao et al. 2020). Some studies focus on the role of non-monetary bounty awards. For example, Zhou et al. (2020) find that non-monetary bounty awards attract more traffic, while Berger et al. (2016) develop models to predict successful bounty awards and response times. High-value awards can attract more participants (Liu et al. 2014) and engage high-ability individuals in specific questions (Boudreau et al. 2011) . However, these studies focus on the isolated impacts of non-monetary awards on answer quality, quantity, or response time, without exploring the underlying mechanisms. Bounty awards, with their unique structure encompassing both external aspects (high competition and rewards) and internal aspects (peer recognition), require a comprehensive investigation. This study aims to address the question of whether bounty awards can synergistically combine extrinsic and intrinsic motivations, attracting more responses while preserving intrinsic motivation and sustaining long-term effort, thereby filling some theoretical gaps.

Temporal Scarcity and Content Contribution

Research on temporal scarcity has primarily focused on task performance and behavioral decision-making. The impact of temporal scarcity on task performance has been explored in the literature, although the findings of these studies are inconclusive. For instance, Karau and Kelly (1992) find that high time pressure can impair performance by consuming cognitive resources. In contrast, Andrews and Farris (1972) reveal a positive relationship between time pressure and job creativity. Drawing on Gardner's (1990) activation theory, other scholars (Baer and Oldham 2006; Byron et al. 2010) suggest that an inverted U-shaped relationship exists between time pressure and performance.

In the consumption domain, time pressure can lead consumers to make quick purchase decisions (Coulter and Roggeveen 2012; Gierl et al. 2008) for discounted products (e.g., through scarcity marketing tactics; Kim et al. 2021). In the context of crowdsourcing contests, some scholars (Al-Hasan et al. 2017; Hofstetter et al. 2018) have investigated the timing strategies for submitting solutions, suggesting that early or late submissions may increase the likelihood of winning. However, few studies have considered the dual impact of time pressure on performance and strategic behavior in the context of bounty incentives. This study aims to provide a new temporal perspective on the content contribution by analyzing contributor behavior during distant and near deadlines.

Hypotheses Development

Compared to the general award, the bounty award is a type of Rank-Order Tournament where only one or a few top participants can win. Research (Straub et al. 2015) has shown that displaying rankings can reduce employee performance because those ranked lower may perceive their chances of winning as lower and subsequently reduce their effort. However, bounty awards are a type of tournament that does not publicly display rankings and are judged solely by the bounty award provider (i.e., the knowledge seeker), with no quantifiable effort required from participants. We consider two possible mechanisms. Firstly, contributors may exhibit optimistic bias and overestimate their chances of winning (Sharot 2011; Weinstein 1980), leading them to participate in the competition for bounty awards even if their time and effort investment remains unchanged. Secondly, opportunistic behavior (Hofstetter et al. 2018) may arise, where participants can piece together an answer to compete for the bounty since both the questions and answers on the platform are visible. This behavior is driven by the lower cost of imitating and replicating answers compared to exerting effort in creating their own and thus they can accept the failure of competition.

Another unique feature of bounty award is that the knowledge seeker acknowledges the participant who has been most instrumental in solving their problem by sacrificing their own reputation points, thereby making the receipt of bounty awards a form of peer recognition. As Gallus (2017) suggests, the substantial recognition and encouragement provided by symbolic awards can be seen as peer recognition and positive feedback for the work of the participant. Jin et al. (2015) find that individuals who receive more peer recognition contribute more knowledge to online Q&A communities. Given the high visibility of bounty awards, participants who receive awards not only gain the attention of the audience but, more importantly, also receive strong recognition from the knowledge seeker directly (through the knowledge seekers' sacrifice of their reputation). This motivation to gain peer recognition may encourage participants to increase their engagement and effort investment. Accordingly, our Hypothesis 1 is as follows:

Hypothesis 1 (H1): Posting a bounty can help users solve the problem in two aspects, that is, increasing the quantity and improving the quality of content contribution.

We seek to examine the impact of bounty amount on user engagement through the lens of motivational intensity theory. This theory, as posited by Wright and Brehm (1989) and Richter et al. (2016), suggests that the willingness to invest effort is influenced by ability, task difficulty, and the likelihood of success. In bounty tasks, the bounty amount equates to the reputation paid by the knowledge seeker. The decision to set a bounty incurs costs for them, who seek to obtain equivalent knowledge and thus expect the reputation paid to match the effort required to answer the question. Consequently, a higher bounty amount may indicate greater difficulty.

According to the motivational intensity theory, as the bounty amount increases within a certain range, participants believe that success is possible and thus will invest more effort to match the increasing difficulty (Richter et al. 2016). However, when the bounty amount becomes too high, participants will view the question as overly challenging and beyond their abilities. In such instances where success is unlikely, individuals will withdraw their efforts (Venables and Fairclough 2009). Consequently, the relationship between bounty amount and content contribution follows an inverted U-shaped curve. Based on this, we propose H2:

Hypothesis 2 (H2): The relationship between the bounty amount and both the quantity and quality of content contribution follows an inverted U-shaped curve.

The stuck-in-the-middle (STIM) effect, as demonstrated by the goal-gradient theory (Emanuel et al. 2022; Hull 1932), reveals a U-shaped pattern in effort allocation. Due to physical and mental exhaustion (Bennie et al. 2018; Lu et al. 2022), individuals often encounter challenges in maintaining high levels of effort over an extended period, and their motivations gradually decline (Sander and Scherer 2009). Previous studies have shown that effort allocation is influenced by costs and benefits involved (Emanuel et al. 2022; Mobbs et al. 2018). Building on this, this study considers the impact of opportunity costs and information acquisition costs on contributors' effort investment, when the deadline is near or far away.

Previous studies (Le Heron et al. 2020; Kurzban et al. 2013) have defined the opportunity cost of performing a focal task as the cost of forgoing action on an alternative task while engaging in the focal task. Typically, this cost is calculated as the value of the alternative task minus the value of the focal option. Importantly, the effort invested in a focal task is inversely related to its opportunity cost (Kurzban et al. 2013). Drawing upon the principle of diminishing marginal utility (Charnov 1976; Mobbs et al. 2018), which suggests that the value of further action on a task tends to decline over time, we can explain the decline in the effort curve when the bounty starts (with minimal temporal scarcity). However, as the deadline approaches, the value of answering questions nearing the expiration date increases due to the imminent loss of the opportunity to provide answers, compared to questions further from the deadline. As a result, the opportunity cost of answering approaching questions (value of questions further from the deadline minus value of approaching questions) becomes minimal (Emanuel et al. 2022). Furthermore, through the informational spillover effect (Al-Hasan et al. 2017), existing answers reduce the cost of obtaining information. This enhances the net benefit of the effort invested towards the end of the bounty period when temporal scarcity is at its maximum (Mobbs et al. 2018).

During the bounty period, when temporal scarcity is low, approaching questions attract the highest number of answers, and participants exhibit the strongest intention to exert effort. As temporal scarcity gradually increases, the value of answering bounty questions follows a trend of diminishing marginal utility, resulting in a gradual decrease in the number of answers and willingness to exert effort. However, as the available time continues to decrease and reaches extreme scarcity, the net benefit of effort becomes highest, leading to an increase in strategic bidding behavior among participants. Consequently, the number of answers and willingness to exert effort rebound to the highest levels. Therefore, we propose a U-shaped relationship between temporal scarcity and the quantity and quality of content contribution. Accordingly, we propose Hypothesis 3:

Hypothesis 3 (H3): There is a U-shaped relationship between temporal scarcity and the quality and quantity of content contribution.

Data and Methodology

Context and Data

To test our hypotheses, we will leverage data from a large Q&A platform Stack Overflow[2] with bounty awards within 7 days. We plan to import the XML data into a relational database to ease further processing. The data dump includes all questions, answers, tags, and log of actions and their rewarded reputation points. We intend to collect all the question posts and relevant data created from 1/1/2017 to 12/32/2021 and eliminated any duplicate data. In addition, we will exclude the samples of "reward existing answer" to eliminate the influence of post-reward on the analysis. To test our hypotheses H1 and H2, we intend to construct a cross-sectional dataset including questions with and without bounties. We

[2] https://archive.org/details/stackexchange

plan to use propensity score matching to correct potential selection bias due to the question characteristics. Regarding Hypothesis 3 (H3), our study centers on the complete duration of the bounty period, which spans 7 days. It is worth noting that on this platform, once a knowledge seeker adds a bounty award to a question with their reputation, they cannot withdraw it. During the bounty period, seekers have the flexibility to accept the "best answer" and allocate the bounty. If the bounty remains unallocated by the end of the bounty period, the platform will reclaim half of the bounty and distribute the other half to the highest-scoring answer. We will employ panel data analysis, incorporating time series data, to examine the influence of temporal scarcity on content contribution.

Key Variables and Econometric Models

Considering the previous study (Yang et al. 2011) and the discretion of the knowledge seeker due to the sacrifice of reputation, we use whether there is the best answer for question i (denoted as $Is\_Solved\_Q_i$) as a proxy variable of content quality. In terms of content quantity, we choose the number of answers that the question i received (denoted as $Num\_A\_Q_i$) as the other dependent variable. Since $Is\_Solved\_Q_i$ is a binary variable that is not continuous or normally distributed, and $Num\_A\_Q_i$ is a count variable with unequal expectation and variance, we will employ logistic regression and negative binomial regression to test the quality and quantity of content contribution, respectively. Both analyses will be conducted using cross-sectional dataset. The models for H1 is represented by Equation 1. When estimating the inverted U-shaped relationship in H2, we add the quadratic term of the independent variable to the models, as shown in Equation 2. And the equations are as follows:

$$DV_i = \alpha_0 + \alpha_1 Is\_Bounty_i + Controls\_1_i + \varepsilon_i \qquad (1)$$

$$DV_i = \beta_0 + \beta_1 Bounty\_Amount_i + \beta_2 Bounty\_Amount_i^2 + Controls\_1_i + \varepsilon_i \qquad (2)$$

where the dependent variable (DV), $Is\_Solved\_Q_i$ is whether there is a best answer to question i in the logistic regression model when testing the factors affecting the quality of content contribution, and $Num\_A\_Q_i$, is the number of answers received of question i in the negative binomial regression model when to test the factors affecting the quantity of content contribution. To examine the impact of bounty awards, our independent variable in Equation 1 is a dummy variable Is_Bounty_i, referring to whether the knowledge seeker posts a bounty of question i, and a continuous variable $Bounty\_Amount_i$ in Equation 2, referring to the bounty amount of question i. $Controls\_1_i$ is some question-variant features as control variables, such as the number of comments ($Q\_num\_comment_i$), the number of vote-ups ($Q\_num\_voteup_i$), the number of tags ($Q\_num\_tag_i$), the title length ($Q\_titlelength_i$), and the number of words in the post body ($Q\_num\_bodywords_i$) for the question when the bounty expires. Finally, ε_i is a mean-zero random error term.

As to the temporal scarcity effect, the quality and quantity of content contribution are transformed to whether there is the best answer in day t for question i (denoted as $Is\_Solved\_D_{it}$) and the number of answers received in day t for the question i (denoted as $Num\_A\_D_{it}$). To estimate the temporal scarcity effect of bounty awards, we intend to build a time series variable, $Scarcity_{it}$, which is defined as the value of the number of days since the start of the bounty period. For instance, on the seventh day of the bounty period, the value of $Scarcity_{it}$ is equal to 7, indicating the highest level of temporal scarcity. The logistic regression model and the negative binomial regression model are then applied to this panel dataset. To examine whether there is a U-shaped relationship, we add the quadratic term of $Scarcity_{it}$ to the models. The equation is as follows:

$$DV_{it} = \gamma_0 + \gamma_1 Scarcity_{it} + \gamma_2 Scarcity_{it}^2 + \mu_i + \omega_t + Controls\_2_{it} + \varepsilon_{it} \qquad (3)$$

where the dependent variable (DV) represents $Is\_Solved\_D_{it}$ and $Num\_A\_D_{it}$, respectively. The independent variable, $Scarcity_{it}$, equals the value of the number of days (t) since the start of the bounty period for question i, and the quadratic term of $Scarcity_{it}$ is considered in this equation. Additionally, we use some time-variant features as control variables, such as the number of comments ($Q\_num\_comment_{it}$), and the number of vote-ups ($Q\_num\_voteup_{it}$) of the bounty questions. Finally, μ_i is the question-fixed effect, ω_t is the time-fixed effect, and ε_{it} is a mean-zero random error term.

Expected Contribution and Future Work

Our research is expected to contribute to the previous studies in several ways. First, the bounty award, as a non-public ranking tournament, can provide incentives similar to monetary rewards, while also counteracting the crowding-out effect of monetary incentives on extrinsic motivation as a peer award. This offers valuable theoretical contributions to the literature on incentive design. Second, temporal scarcity, as a trigger for strategic behavior, provides a new temporal perspective on motivation in the context of content contribution. Additionally, the practical implications of this study are substantial. The empirical findings can inform the optimization of reward design in terms of both the amount and timing, establishing a reciprocal relationship between content production and consumption. This can ultimately lead to a win-win situation among the platform, seeker, and contributor, enhancing the overall effectiveness and efficiency of the system.

Our study has certain limitations. In terms of data and methodology, we plan to incorporate random experiments and employ strategic behavior modeling to enhance the robustness of the results. We also intend to investigate the role of bounty awards in offsetting the crowding-out effect on intrinsic motivation by distributing surveys to online users. In terms of research design, to examine the motivational effects of bounty rewards for different reasons, we intend to categorize bounties and conduct a heterogeneous treatment effect (HTE) analysis. Furthermore, we recognize that the quality of bounty questions may also impact participants' performance with the temporal scarcity effect. Therefore, in future work, we plan to explore the moderating effect of information quality on the U-shaped relationship between temporal scarcity and content contribution. Additionally, besides examining the quality and quantity of content contributions, we also plan to conduct a more comprehensive exploration of the textual attributes of the content.

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