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Answers are wanted: The role of bounty amount and temporal scarcity in knowledge contribution

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ABSTRACT

The challenge of encouraging knowledge contribution has led many knowledge-sharing communities to implement incentive mechanisms. While rule-based incentives are widely used, bounty awards—a novel form that allows knowledge seekers to set customized reward amounts and is subject to a fixed expiration period—remain underexplored. We investigate how these two features of bounty awards influence knowledge contribution, drawing on the idea that bounty amount signals both reward attractiveness and question difficulty, while expiration deadline introduces temporal scarcity. Using data from Stack Overflow, we assess outcomes in terms of answer quantity, average quality, and problem-solving likelihood. We find that offering a bounty award increases the quantity and quality of answers, as well as the likelihood of problem-solving. However, the bounty amount yields diminishing marginal returns in answer quantity, while it has a positive and linear effect on the relevance to the question. Meanwhile, it exhibits an inverted U-shaped effect on problem-solving likelihood and answer scores—possibly due to the perceived difficulty of higher-reward questions. Temporal scarcity exhibits a U-shaped relationship with both quantity and solving likelihood, while the U-shaped pattern in answer quality is only partially supported. We also uncover insightful heterogeneous effects, demonstrating that high-quality or under-answered questions may intensify the impact of bounty amount on answer volume, while low-reputation contributors exhibit greater sensitivity to temporal scarcity regarding answer volume. Our study advances the understanding of incentive design in knowledge-sharing communities by theorizing and empirically validating how bounty awards—with their seeker-customized amounts and time-sensitive nature—shape contributor behavior.

1. Introduction

Sharing knowledge on online platforms plays a crucial role in facilitating knowledge storage. As of June 2024, Wikipedia boasts close to 47 million registered users. However, only a small fraction (113 thousand users with editorial activity within 30 days) contributes actively to the platform daily.[1] To motivate users to contribute and sustain growth, many UGC platforms, such as Wikipedia, Stack Overflow, and Quora, use a diverse range of point systems to signal user activity and contributions. For instance, Reddit utilizes a point system known as "Karma," Stack Exchange employs "Reputation Points," and on Duolingo, user progression is tracked through "XP." These systems are examples of rule-based incentives, which refer to predefined reward mechanisms where contributors earn points or rewards based on specific, objective criteria, such as answering a question or receiving a certain number of upvotes. These incentives are automatically triggered when contributors meet the established rules, ensuring transparency and consistency in the reward distribution process. Previous literature has explored the impact of virtual rule-based incentives on content contribution, such as reputation points [1,2], gamified rankings [3], hierarchical structures [4], and badges [5–7]. While these incentives aim to drive contributors to answer general questions, more than 30% of questions on Stack Overflow remain unanswered promptly. Therefore, incentivizing contributors to help knowledge seekers solve specific problems more quickly is a critical challenge for content production.

Due to the varied needs and preferences of knowledge seekers on these platforms, rule-based general awards have limited effectiveness in solving specific problems. Therefore, platform operators such as Stack

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

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Overflow have introduced an incentive mechanism—the bounty award—offering seeker-customized reputation points as a reward to accelerate and enhance the assistance provided to knowledge seekers. As shown in Fig. 1, on Stack Overflow, a bountied question differs from regular questions in several ways. For instance, the knowledge seeker can customize the bounty amount based on factors such as the effort required to answer the question, with an example amount of 250 reputation points. Additionally, responses must be submitted within a limited time frame, typically seven days. The platform also displays a countdown indicating the time remaining before the bounty expires, such as "The bounty expires in 5 hours."

Bounty awards differ from rule-based rewards in several significant ways. First, the amount of a bounty award is seeker-customized rather than platform-controlled. While rule-based incentives follow standardized algorithms or fixed thresholds set by the platform, such as reputation points for accepted answers [3–5], the bounty amount is determined by the knowledge seeker based on perceived task importance, urgency, and budget. Thus, prior findings on the effectiveness of rule-based incentives may not apply to seeker-customized bounty mechanisms. Within the broader category of seeker-customized financial rewards, such as those found in crowdsourcing contests, existing studies have shown that reward amounts can influence participation by signaling task value, difficulty, or urgency [8–10]. The impact is often nonlinear—excessively high rewards may reduce marginal utility, encourage copycat behavior, or heighten competition to the point of discouraging individual participation [11]. Nonetheless, these insights are drawn from financial contest environments, and their findings may not generalize directly to bounty awards in knowledge-sharing communities. Therefore, a separate examination of bounty-specific incentive effects is warranted.

Second, bounty awards introduce a time constraint that may influence contributors' performance and decision-making throughout the bounty period. The scarcity of available time can create subjective pressure and a sense of urgency, affecting contribution dynamics through cognitive mechanisms. In learning and work tasks, time pressure has been found to influence cognitive processing, though existing research findings are inconsistent [12–16]. Temporal scarcity, as a perceived urgency, forces individuals to make decisions within a limited time frame [17]. For instance, marketing literature has investigated how insufficient time prompts consumers to make quick purchase decisions [16,18,19], while crowdsourcing contest research examines how timing strategies, such as early or late submissions, can increase the likelihood of winning [20,21].

Although rule-based reputation incentives (e.g., badges, scores) [1,3,5,7] and generalized seeker-customized financial rewards, such as those implemented in crowdsourcing contests and bug bounty programs [11,12] have been studied widely, few have systematically investigated bounty awards as a distinct incentive combining seeker-customized amounts and temporal constraints. In light of this, this paper addresses three research questions. (1) To what extent are bounty awards effective in motivating greater content contribution, in terms of quantity and quality, as well as increasing the likelihood of problem-solving? (2) Is the incentivizing effect on content contribution stronger with a higher bounty amount? (3) How does the temporal scarcity associated with bounty awards influence content contribution?

To explore these questions, we utilize data from Stack Overflow, including all questions, answers, tags, and related information between 1 January and 31 December 2020.[2] In this paper, we construct a cross-sectional dataset and a panel dataset to examine our hypotheses. Our findings show that (1) offering a bounty award can motivate participants effectively to contribute more answers, improve the average quality of answers, and increase the likelihood that the problem will be solved; (2) there is an inverted U-shaped relationship between the bounty amount and two key outcomes, the likelihood of problem-solving and answer scores (net votes reflecting user evaluation), but for the number of answers, the relationship follows an initial increase and then stabilizes. For textual relevance between answers and their questions, we find a positively linear relationship rather than an inverted U-shape; (3) there is a U-shaped relationship between temporal scarcity and the number of answers and the likelihood of problem-solving, indicating increased contributor engagement at the beginning and end of the bounty period, whereas answer quality initially decreases and then stabilizes, showing no improvement under extreme temporal scarcity.

Our study contributes to prior research in several ways. First, it conceptualizes bounty awards as a novel incentive mechanism that extends traditional rule-based systems by combining seeker-customized reward amounts with temporal dynamics, enriching the diversity of incentive designs in knowledge-sharing platforms. Second, it contributes to the motivation literature by elucidating the unique mechanism of the bounty amount. As a reward feature, the seeker-customized reputational amount functions through the tension between its strength of perceived value and question difficulty. This helps explain the non-monotonic effects of bounty amount on contribution behaviors, thereby advancing our understanding of how reward features shape individual motivation. Third, it extends the effects of temporal scarcity from workplace, educational, and marketing contexts to knowledge-sharing, enriching the motivation literature.

The rest of this paper proceeds as follows. In Sections 2 and 3, we first review the relevant literature and then develop our hypotheses. Section 4 presents our data collection details, measurements of the main variables, and model specifications. In Section 5, the empirical results of the main hypotheses are presented. Section 6 shows the results of robustness checks and further discussions. In the last section, we conclude.

2. Literature review

2.1. Bounty awards

On digital platforms, content contribution is typically incentivized through two major mechanisms: reputation-based incentives and financial incentives [8,22,23]. Reputation incentives, such as badges [5,7], scores [1], and leaderboard rankings [3], motivate contributors through peer recognition [24] and the accumulation of social capital [1]. Financial incentives [25], in contrast, offer direct monetary compensation for task completion, such as writing reviews. Bounty awards represent a hybrid form that combines features from both.

On knowledge-sharing platforms, bounty awards are seeker-customized rewards that motivate contributors to provide high-quality answers. Similarly, on other platforms such as crowdsourcing contests and bug bounty programs, task-specific, seeker-customized financial rewards are offered to attract participants and stimulate task completion [8,10,26–28]. In crowdsourcing contests, these incentives encourage participation, attract diverse solvers, and improve solution quality, though effects may plateau [8,26]. In bug bounty programs, the effectiveness of seeker-customized financial rewards is shaped by governance: Formal rules and relational governance boost hacker participation, while the incentives themselves enhance compliance, engagement, and system security [27,28]. Although bounty awards share some features with financial incentives, they differ fundamentally by being non-monetary in nature, and the context of knowledge contribution differs from that of crowdsourcing or bug bounty programs.

Bounty awards also share certain similarities with reputation-based incentives, as both are designed to motivate voluntary contributions on knowledge-sharing platforms through symbolic and status-related rewards. Prior studies have examined rule-based reputation systems extensively, including point-based hierarchies [4], expert badges [5], and leaderboard placements [29]. These mechanisms are typically rule-based, providing standardized forms of recognition for sustained

[2] To ensure that bountied questions have received sufficient answers, and that the data has reached a stable state, we selected data from earlier years.

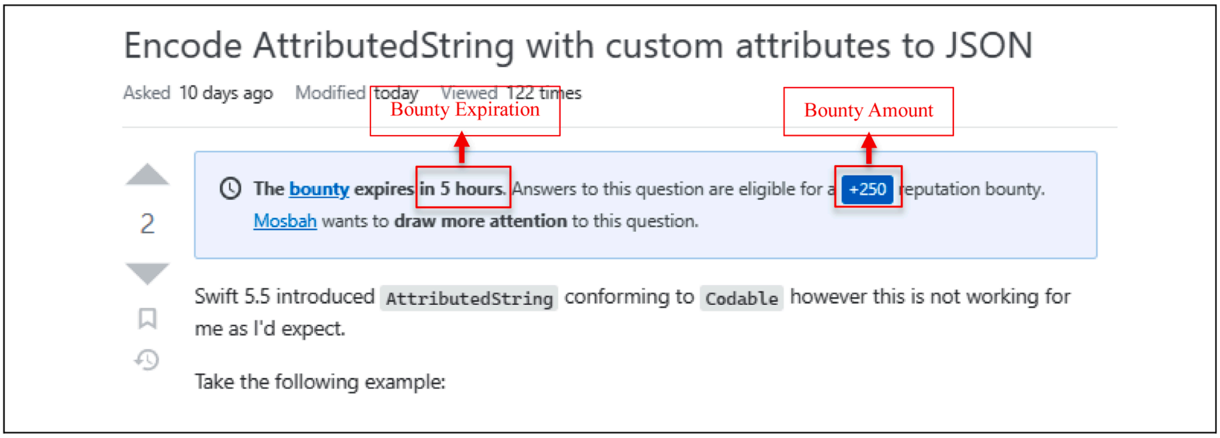


Fig. 1. A question posted on Stack Overflow with bounty.

platform engagement and high-quality knowledge contributions [1,3]. Such recognition not only satisfies contributors' intrinsic motivations for self-efficacy and community identity [2] but also encourages continued participation through social reinforcement and symbolic prestige [7]. Although the bounty mechanism shares features with reputation-based incentives, it differs fundamentally in two key ways: it is seeker-customized—knowledge seekers determine the presence, amount, and recipient of the reward independently—and it is temporally dynamic, operating within a defined time window that explicitly signals reward expiration and imposes temporal constraints absent in conventional reputation systems.

Beyond the two research streams on financial incentives and reputation-based mechanisms that share certain features with bounty awards, direct investigations of bounty awards in knowledge-sharing platforms remain relatively limited. Several studies have examined whether the presence of a bounty affects contributor engagement, finding that bounties tend to increase response rates and reduce answer latency [30–32]. Other work has shown that a higher bounty amount is generally associated with faster and sometimes higher-quality answers [30,33]. While these studies offer initial evidence of the effectiveness of bounty mechanisms, they treat bounty awards primarily as a generic form of extrinsic incentive. They fail to explain how the core characteristics of bounty awards shape behavior distinctively. The seeker-customized design, where the reward originates from a peer, transforms the bounty into a salient signal of the question's value and the knowledge seeker's appreciation, going beyond the standardized recognition of rule-based systems [3,5]. Concurrently, the temporally dynamic structure, with its explicit deadline, creates a unique sense of urgency and competition not found in reputation mechanisms without time constraints [8,26,34]. The theoretical gap lies in understanding how these two mechanisms—a potent seeker-customized value signal and a time-bound urgency—work together to drive contributor behavior, a linkage that prior studies have not addressed.

2.2. The role of reward amounts

One of the distinctive features of bounty awards is that they allow knowledge seekers to customize the reward amounts. This customization introduces a level of complexity that distinguishes bounty incentives from fixed, rule-based rewards. Prior studies on the effects of reward amounts have highlighted how the amount of rewards, across both rule-based reputation systems and seeker-customized financial incentives, shapes contributor motivation, underscoring both their potential and the complexity of their impact.

One stream of literature relevant to our study focuses on reward amounts in rule-based reputation systems. In such systems, rule-based rewards, such as points or badges, are automatically allocated based on predefined behavioral triggers [3–5]. This standardized structure makes the reward amounts predictable, enabling contributors to form stable expectations. Studies show that higher virtual reward amounts (e.g., higher-tier reputation points, which correspond to dozens or hundreds of points as compared with lower-tier single-digit points [3], or more prestigious badges [5]) can motivate greater participation and higher-quality contributions, though the marginal effects may diminish beyond certain thresholds [5].

Another stream of literature relevant to our research examines seeker-customized financial reward amounts, such as those employed in crowdsourcing contests and bug bounty programs. These incentives provide direct monetary compensation based on task performance, and their amounts possess explicit economic value, enabling contributors to make participation decisions through a cost–benefit analysis [8,26,34]. A larger financial reward amount typically signals greater task difficulty or urgency, thereby attracting more participants and heightening competition [9]. Studies have shown that larger monetary amounts not only boost the number of submissions [11] but also influence the timing, quality, and strategic behavior of contributors [9,34]. Excessively large reward amounts may backfire under high uncertainty, leading to lower marginal utility or copycat behavior [8], highlighting the complexity of interpreting monetary incentive signals in competitive environments.

The foregoing discussion reveals that the amount operates through fundamentally different mechanisms in rule-based reputation systems than in seeker-customized financial incentive systems. Table 1 summarizes these prior findings and highlights how the present study differs from this literature.

As shown in Table 1, prior research has focused primarily either on the rule-based reputation reward amounts or on the seeker-customized financial reward amounts, establishing two distinct mechanistic pathways. The preceding review suggests that rule-based amounts typically exert a linear influence through predictable signaling [3,5], whereas seeker-customized financial amounts often demonstrate a positive relationship with contributions up to a point [8,9,33], beyond which the effects may plateau or reverse due to crowding-out or heightened competitive risks under uncertainty [11,26,34]. This contrast highlights the theoretical novelty of bounty amount as a hybrid form of seeker-customized reputational rewards. Its non-monetary nature may avoid the motivational crowding-out of large financial rewards [8], while its customized nature may overcome the lack of task-specificity in rule-based reputation [5]. Thus, the bounty amount, as a non-monetary and question-specific reward feature, likely operates through a distinct mechanism. A larger bounty amount signals the question's attractiveness and perceived value on one hand, while also indicating greater difficulty and attainment uncertainty [30] on the other—a combined mechanism that has yet to be fully explored.

Table 1
Summary of reward amount effects under reputation- and financial-based incentives.

Incentive Type	Operationalization of Reward Amounts	Paper	Findings on the Dependent Variables			Mechanism	Context
			Quantity of Content Contribution	Quality of Content Contribution	Likelihood of Problem-Solving		
Financial rewards	Seeker-customized money	Boudreau et al. (2011) [8]	Positive	Positive (under low-uncertainty); inverted U-shape (under high-uncertainty)	-	Crowding-out effect	Crowdsourcing contests
		Huang et al. (2012) [9]	Positive	Positive		Expected utility theory	
		Liu et al. (2014) [11]	Marginal decline	Positive		Revenue equivalence theorem	
		Harper et al. (2008) [33]	-	Positive		Not mentioned	
		Chen et al. (2010)[34]	Positive	Inverted U-shape		Incentive theory	
		Liu et al. (2021) [26]	Inverted U-shape	-		Crowding-out effect	
Reputation rewards	Rule-based reputation	Wei et al. (2015) [3]	Positive	Positive	-	Incentive theory	Knowledge-sharing
		Cavusoglu et al. (2021) [5]	Positive	Type-dependent Positive		Signaling	
Bounty awards	Seeker-customized reputation	Our study	√	√	√		Knowledge-sharing

2.3. Temporal scarcity

Another important feature of bounty awards is their limited duration. We review literature on temporal scarcity and its implications for user engagement and effort allocation. In existing literature, temporal scarcity manifests primarily through time pressure—a subjective experience involving not only the availability of time but also other psychological and physiological variables, such as the importance and complexity of the tasks to be handled [35]. On one hand, the impact of time pressure on task performance has been explored, though the findings of these studies remain inconclusive. For instance, Karau and Kelly [12] find that high time pressure can impair performance by consuming cognitive resources. In contrast, Andrews and Farris [13] reveal a positive relationship between time pressure and job creativity. Drawing on Gardner's [36] activation theory, other scholars [14,15] suggest that an inverted U-shaped relationship exists between time pressure and performance. According to temporal motivation theory [19], a deadline reminder reduces procrastination and increases the probability of assignment completion.

On the other hand, time pressure may influence individual choice preferences. It acts as a specific constraint that requires individuals to make decisions within a limited time frame [17]. Existing literature on time pressure [37,38] focuses primarily on situations where individuals do not have sufficient time to make decisions. For example, time pressure can lead consumers to complete a purchase decision step in a few seconds [15,39] for discounted products (e.g., through scarcity marketing tactics) [18], while the step itself typically requires more time. Similarly, literature on crowdsourcing contests [20] has investigated the timing strategies for submitting solutions, suggesting that early or late submissions may increase the likelihood of winning.

While existing studies have explored the effects of time pressure on task performance and decision-making, they focus primarily on workplace, educational, and marketing contexts. Little is known about how time pressure shapes knowledge contribution behavior on knowledge-sharing platforms, leaving a critical gap in the literature.

3. Hypothesis development

Bounty awards are extra incentives that target solving specific problems on user-generated content platforms. This paper aims to study how content contribution changes in response to bounty awards and their two features. In this section, we develop research hypotheses regarding three aspects: (1) the effect of offering bounty awards on content contribution; (2) the effect of bounty amount; and (3) the role of temporal scarcity arising from the limited active period of bounty awards.

3.1. The effect of offering bounty awards on content contribution

Compared to questions without rewards, bounty awards serve as a direct incentive for contributors, as receiving a bounty enhances their platform reputation. As a result, contributors are more motivated to provide additional responses [34]. At the same time, this incentive can also trigger opportunistic behavior [21], where contributors may synthesize answers by compiling publicly available content in an attempt to secure the award [29], further increasing the number of answers. Additionally, bountied questions feature a distinct visual label, making them more prominent and attracting greater attention, which in turn boosts their viewership. According to Goes et al. (2014) [40], a larger audience size positively influences the number of answers. Based on this, we propose Hypothesis 1a:

Hypothesis 1a. Offering a bounty award increases the number of answers.

In contrast to rule-based rewards, bounty awards function as a form of peer recognition [29], where the knowledge seeker selects the most helpful answer and grants reputation-based rewards to the contributor. On knowledge-sharing platforms, intrinsic motivation plays a crucial role in driving greater effort and enhancing content quality. Specifically, contributors who receive peer recognition, as a form of intrinsic incentive, are more likely to contribute valuable knowledge [41] and generate more innovative content [24]. As a result, the benefits of peer recognition lead to an overall improvement in the average quality of responses. Furthermore, the combined increase in both answer quality and quantity enhances the likelihood of problem-solving. Thus, we propose Hypothesis 1b and Hypothesis 1c:

Hypothesis 1b. Offering a bounty award increases the average quality of answers.

Hypothesis 1c. Offering a bounty award increases the likelihood of problem-solving.

3.2. The effect of bounty amount on content contribution

We posit that the effect of bounty amount on content contribution operates through two competing mechanisms. On one hand, a higher bounty amount increases the attractiveness of a task to contributors, as a greater reward enhances the perceived value (valence) of the task, making it more desirable to complete [42]. On the other, a higher bounty amount often signals greater task difficulty. According to Haans et al. (2016) [43], the interaction between two latent linear functions—one positive and one negative—results in either an inverted U-shaped or a U-shaped curve. Motivational intensity theory provides a useful framework for understanding this nonlinear relationship. Motivational intensity theory [44,45] suggests that, in goal pursuit, both task value and perceived likelihood of success influence motivation and effort allocation. Specifically, when individuals perceive a task as achievable, they exert more effort as the task value increases. However, when a task is perceived as overly difficult, exceeding their capabilities, they are likely to withdraw their effort.

In the context of bounty tasks, a higher bounty amount enhances task value, which can attract more contributors. When the bounty amount increases within a certain range and remains within the contributor's capability, the positive mechanism of increased task value dominates, leading to more contributors submitting more responses. However, a higher bounty also implies greater task difficulty and higher expectations from the knowledge seeker. Once the bounty amount exceeds a critical threshold, contributors may perceive the task as too difficult, at which point the negative mechanism associated with task difficulty prevails. As a result, some contributors may choose to withdraw, and the number of answers received by the knowledge seeker declines. Thus, we propose Hypothesis 2a:

Hypothesis 2a. There is an inverted U-shaped relationship between the bounty amount and the number of answers.

Similarly, when the bounty amount increases within a certain range, individuals are motivated to obtain enhanced task value. As they recognize greater task value, they weigh the trade-off between effort and reward. According to expectancy-value theory [42], individuals exhibit stronger motivation when they anticipate higher returns, such as increased bounty amounts. Consequently, contributors dedicate more time and cognitive resources to engage in deeper information processing, reducing superficial or perfunctory responses and thereby enhancing content quality. However, once the bounty amount surpasses a critical threshold, the negative effect of task difficulty becomes dominant, prompting contributors to invest less time and effort in content contribution. As a result, as effort investment first increases and then decreases, the average quality of answers provided by contributors follows the same inverted U-shaped pattern. Thus, we propose Hypothesis 2b:

Hypothesis 2b. There is an inverted U-shaped relationship between the bounty amount and the average quality of answers.

Since both the number of answers and the average quality of answers follow an inverted U-shaped pattern with an increasing bounty amount, the likelihood of problem-solving is expected to exhibit a similar trend. Thus, we propose Hypothesis 2c:

Hypothesis 2c. There is an inverted U-shaped relationship between the bounty amount and the likelihood of problem-solving.

3.3. The effect of temporal scarcity on content contribution

As the time constraint for task completion becomes more pressing, individuals experience a heightened sense of temporal scarcity. Temporal scarcity influences contributors' participation and effort through two opposing mechanisms. On one hand, it gradually depletes their cognitive resources [46,47], which creates a negative effect over the entire task period. On the other, it affects attention allocation. Specifically, there is a critical threshold. As long as the available time has not decreased past this point, it remains sufficient for task completion, and individuals do not perceive a sense of urgent pressure. According to previous studies [48,49], the mere urgency effect shifts individuals' attention from task outcomes (payoff) to time constraints, increasing their tendency to prioritize urgent tasks. In practice, however, deadlines are often associated with meaningful consequences, such as rewards or punishments, which amplify their motivational impact [50]. This suggests that in the latter half of a task period, apart from the negative effect of cognitive resource depletion, there is also a positive effect stemming from increased attentional focus on urgent tasks and the incentive associated with potential rewards.

In the context of bounty awards, the expiration date of the bounty defines the perceived time constraint experienced by contributors. Although knowledge seekers retain discretion over the exact timing of awarding, prior literature suggests that contributors act as if the award will most probably be issued at the expiration date [30].[3] Thus, the deadline and the expected award timing effectively overlap, creating a focal point that concentrates contributors' attention on the end of the bounty period. Early in the window, ample time allows contributors to allocate sufficient cognitive resources, encouraging broad participation and a high volume of answers. As time passes, cognitive resources diminish, leading to fewer answers. Yet, when time becomes extremely scarce, contributors experience a heightened sense of urgency, driven both by the incentive associated with potential rewards [50] and by temporal scarcity that redirects their attention from other tasks to the urgent bounty task [48,49,51], ultimately increasing the number of answers.

We hypothesize that the positive effect of urgency on attention dominates in the latter half of the task period, leading to an increase in answer quantity as the bounty deadline approaches. Thus, we propose Hypothesis 3a:

Hypothesis 3a. There is a U-shaped relationship between temporal scarcity and the number of answers.

At the beginning of the bounty period, contributors' cognitive resources are fully available, allowing them to dedicate their full capacity to producing high-quality answers. As time elapses and cognitive resources become progressively depleted, answer quality declines. However, when time becomes extremely scarce, two opposing effects emerge. On one hand, severe cognitive depletion may prevent contributors from crafting high-value answers. On the other, the mere urgency effect may lead contributors to prioritize urgent tasks. An increase in task urgency imposes choice constraints on individuals [52–55]. When faced with such constraints, individuals often abandon familiar, proven

[3] Statistical results show that even though high-quality answers are submitted throughout the bounty window, awards are heavily concentrated on its final day (details are omitted due to space limitations). This supports the claim that bounty expiration date functions as both the formal temporal limit and the focal point for award allocation, effectively coinciding with the end of the bounty window.

solutions [56] and break away from habitual thinking in search of novel approaches, thereby enhancing creativity [57,58]. Consequently, temporal scarcity activates a constraint mindset, prompting participants to deviate from conventional thinking and generate more creative responses. Meanwhile, a deadline accompanied by meaningful consequences (such as the potential of a bounty award) further amplifies the effect of urgency [50]. As a result, answer quality improves. Based on this, we propose Hypothesis 3b:

Hypothesis 3b. There is a U-shaped relationship between temporal scarcity and the average quality of answers.

Since temporal scarcity exhibits an initial decline followed by an increase in both answer quantity and average answer quality, we expect that the likelihood of problem-solving follows a similar pattern. Thus, we propose Hypothesis 3c:

Hypothesis 3c. There is a U-shaped relationship between temporal scarcity and the likelihood of problem-solving.

It is important to acknowledge that other theoretical mechanisms may plausibly influence how contributors respond to temporal scarcity, yet they offer fewer convincing explanations for the U-shaped pattern proposed here. One alternative explanation is rank visibility, as questions near expiration are displayed more prominently. However, participation and effort are mainly driven by task value, expected rewards, and social incentives, rather than exposure alone [1,59]. Another possibility is social learning, where contributors observe prior answers. This may reduce redundant effort but mainly causes convergence rather than quality improvement, and platforms often reward originality over imitation, limiting its ability to explain the late-stage resurgence [20,21]. Finally, procrastination may also describe delayed action under deadlines. Yet procrastination reflects avoidance-driven delay and often results in hastily produced, lower-quality outcomes [60,61]. Taken together, while rank visibility, social learning, and procrastination may contribute to some extent, each provides a less convincing account of the U-shaped effects of temporal scarcity on both the quantity and quality of contributions.

4. Data and methodology

4.1. Context and data

On Stack Overflow, a large Q&A platform where bounty awards are effective for 7 days, knowledge seekers offer bounties to attract answers to particularly challenging or urgently needed questions.[4] They can freely set the bounty amount within a range of 50 to 500 reputation points. During the bounty period, knowledge seekers have the flexibility to accept the "best answer" and allocate the bounty accordingly. Contributors, in turn, are fully informed of the bounty's existence, amount, and time constraints before deciding whether and when to participate. Notably, on this platform, once a knowledge seeker adds a bounty award to a question with their reputation points, they cannot withdraw it. If the bounty remains unallocated upon expiration, the platform will reclaim half the amount and automatically award the other half to the highest-scoring answer.

To test our hypotheses, we leveraged data from Stack Overflow.[5] We imported the XML data into a relational database to ease further processing. The data dump includes all questions, answers, tags, and a log of actions and their rewarded reputation points. We collected all the question posts and relevant data (tags, answers, votes, bounty information, etc.) created from 1 January to 31 December 2020,[6] and eliminated any duplicate data. To test H1 and H2, we constructed a cross-sectional dataset including questions with and without bounties. We used coarsened exact matching and propensity score matching to mitigate potential selection bias due to the question characteristics. Regarding Hypothesis 3, we assessed the influence of temporal scarcity on content contribution using panel data analysis. To ensure that contributor behavior was meaningfully shaped by the presence of active bounty incentives, we focused only on the periods during which the bounty was still available. Specifically, once a knowledge seeker manually awarded the bounty at any point within the seven-day bounty window, the incentive was no longer in effect, and contributors were no longer subject to time pressure related to bounty availability. Accordingly, we constructed an unbalanced panel dataset in which each bountied question was observed daily until the bounty was awarded. For example, if a bounty was awarded on Day 4, we retained only Days 1–4 for that question and excluded the remaining days. Irrespective of this, a substantial portion of bounties were awarded on Day 7, largely coinciding with the expiration date of the bounty. The final dataset comprises 100,803 bountied question–day observations that reflect valid exposure to temporal scarcity.

4.2. Key variables and econometric models

Guided by prior research [62] and considering the discretion exercised by knowledge seekers when offering a bounty award, we use $Solved_i$ as the measure of problem-solving, which is a binary variable equal to 1 if a best answer is accepted for question i (and 0 otherwise). To capture the quantity of content contribution, we use the number of answers that question i received (denoted as $Answers_i$) as a proxy. For answer quality, drawing on established literature on quality measurement [8,63], we adopt two indicators:[7] answer score[8] and textual relevance to the question. At the question level, we compute the average score ($Score_i$) and the average textual relevance ($Relevance_i$) across all answers received by question i.

Since $Solved_i$ is a binary variable that is not continuous or normally distributed, and $Answers_i$ is a count variable with unequal expectation and variance, we employ logistic regression and negative binomial regression to test the likelihood of solving the problem and the number of answers, respectively. For the dependent variable ($Score_i$) that approximates a normal distribution, we employ a linear regression model. For the continuous variable ($Relevance_i$) that exhibits skewed distributions and values ranging between 0 and 1, we use a beta regression model. All analyses were conducted using a cross-sectional dataset. The model for testing H1 is Model (1). When estimating the inverted U-shaped relationship in H2, we add the quadratic term of the independent variable ($Amount_i^2$) to the model, as shown in Model (2). The equations are

[4] In some cases, a bounty is added to an existing answer when the knowledge seeker finds it exceptionally helpful and wants to reward the contributor as a token of appreciation. We excluded such instances from our sample because, in these cases, the contributor was not influenced by the bounty award incentive, as the answer had already been completed.

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

[6] Data were collected in March 2022 and covered the period from 2019 to 2022. We restricted our main analysis to the 2020 cohort to ensure a sufficient observation window for the complete evolution of bountied questions. We excluded 2021 and 2022 from the primary sample because their recentness led to substantial right-censoring (i.e., a low volume of fully resolved cases). However, robustness checks using the 2019 and 2021 samples (the latter despite its censoring limitations) yielded results consistent with our main findings, suggesting that our results are not driven by specific time windows.

[7] While answer length has been used as a quality proxy in some studies, we treat it as a measure of contributor effort because it more directly reflects time and cognitive investment. Related analyses are presented in the Appendix.

[8] In this study, we use the score to represent question quality, as it reflects user feedback on the answers. Unlike $Upvotes_i$, which measures the number of upvotes, $Score_i$ is calculated as the number of upvotes minus the number of downvotes, providing a more comprehensive evaluation.

$$DV_i = \alpha_0 + \alpha_1 Bounty_i + \textbf{Controls\_1}_i + \varepsilon_i, \tag{1}$$

$$DV_i = \beta_0 + \beta_1 Amount_i + \beta_2 Amount_i^2 + \textbf{Controls\_1}_i + \varepsilon_i, \tag{2}$$

where the dependent variables (DV_i) represent $Solved_i$, $Answers_i$, $Score_i$, and $Relevance_i$, respectively. The independent variables are defined as follows. In Model (1), $Bounty_i$ is a dummy variable that equals 1 if the knowledge seeker offers a bounty on question i (and 0 otherwise). In Model (2), $Amount_i$ represents the bounty amount offered for question i (scaled by 1/100). $\textbf{Controls\_1}_i$ are some question-related and user-related features as control variables, including the title length of question i ($TitleLength_i$), the number of words in the body of question i ($BodyLength_i$), the number of tags of question i ($Tags_i$), the number of days between the creation of question i and the receipt of its first answer ($FirstAnswer_i$), the number of existing answers received for question i before the start of the bounty period ($ExistingAnswers_i$), a binary variable that equals 1 if the knowledge seeker of question i had previously posted a bountied question ($Before_i$), the number of days between the knowledge seeker's registration and the creation of question i ($UserDays_i$), the knowledge seeker's reputation before the creation of question i ($Reputation_i$), the number of upvotes received by the knowledge seeker before the creation of question i ($Upvotes_i$), and the number of bountied questions posted by the knowledge seeker before the creation of question i ($ExistingBounty_i$). We also utilize the latent Dirichlet allocation (LDA) model to extract the topic of each question ($Topic_i$) as a control variable. Variables including $TitleLength_i$, $BodyLength_i$, $Tags_i$, $FirstAnswer_i$, $ExistingAnswers_i$, $UserDays_i$, $Reputation_i$, $Upvotes_i$, and $ExistingBounty_i$ are log-transformed to normalize their distributions. For $Score_i$, which contains negative values, we add a constant shift before applying the logarithmic transformation to ensure valid domains. Finally, ε_i is a mean-zero random error term.

When testing the role of temporal scarcity in answering questions (i.e., H3), we restrict our sample to questions with bounty awards. Given that the bounty period lasts for 7 days, we construct a question-day panel dataset indexed by question i and day t, where t denotes the number of days elapsed since the bounty was created. As to the dependent variables, we operationalize the likelihood of problem-solving ($Solved_{i,t}$) as a binary indicator equal to 1 if a best answer is accepted for the question i on day t (and 0 otherwise). To capture the dynamics of content contribution, we measure the quantity and quality of answers received on day t using three indicators: the number of answers to question i ($Answers_{i,t}$), the average answer score to question i ($Score_{i,t}$), and the average textual relevance between question i and its associated answers ($Relevance_{i,t}$). Our key independent variable, $Scarcity_{i,t}$, is defined as the number of days elapsed since the bounty was created. For instance, on the seventh day of the bounty period, the value of $Scarcity_{i,t}$ is equal to 7, indicating the highest level of temporal scarcity.

To examine whether there is a U-shaped relationship as proposed in H3, we add the quadratic term ($Scarcity_{i,t}^2$) to the model, as shown in Model (3). We include the question-fixed effects, day-fixed effects, and topic-fixed effects to Model (3) to address potential heterogeneity. The equation is

$$DV_{i,t} = \gamma_0 + \gamma_1 Scarcity_{i,t} + \gamma_2 Scarcity_{i,t}^2 + \mu_i + \omega_t + \delta_i + \textbf{Controls\_2}_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where the dependent variables ($DV_{i,t}$) represent $Solved_{i,t}$, $Answers_{i,t}$, $Score_{i,t}$, and $Relevance_{i,t}$, respectively. The independent variables are $Scarcity_{i,t}$ and the quadratic term, $Scarcity_{i,t}^2$, in this equation. Additionally, we use some time-variant features as control variables, including the number of answers to question i on day t-1 ($Answers_{i,t\text{-}1}$), the number of comments to question i on day t ($Comment_{i,t}$), and the number of upvotes to questions i on day t ($Upvotes_{i,t}$). The variable $Answers_{i,t\text{-}1}$ controls for the potential influence of prior answers on subsequent contributor behavior. Variables, $Comment_{i,t}$ and $Upvotes_{i,t}$, are log-transformed to normalize their distributions. For $Score_{i,t}$, which contains negative values, we added a constant shift before applying the logarithmic transformation to ensure valid domains. Finally, μ_i, ω_t, and δ_i denote the question, day, and topic fixed effects, respectively. $\varepsilon_{i,t}$ is a mean-zero random error term.

Tables 2 and 3 provide a comprehensive overview of the key variables. According to Table 2, only 46.5 % of questions have an accepted best answer, and the average number of answers per question is 1.535. These statistics indicate that a significant portion of questions on Stack Overflow remain unresolved, thereby highlighting the importance of examining the bounty incentive mechanism.

5. Empirical results

5.1. The effect of offering bounty awards on content contribution

Table 4 displays the regression coefficients and the robust standard errors in parentheses for four dependent variables. As seen in the first row, the coefficients of the key independent variable $Bounty_i$ are all significant and consistent with our hypotheses, suggesting that content contribution improves with the provision of bounty awards.

Particularly, as shown in Columns (1) and (2) of Table 4, the number of answers received and the likelihood of receiving the best answer per question significantly increase when knowledge seekers offer a bounty award. The coefficients of $Bounty_i$ related to $Answers_i$ and $Solved_i$ are 0.283 and 0.140, respectively, both positive and significant at the 0.01 level. For answer quantity ($Answers_i$), which employs a negative binomial model, the incidence rate ratio is 1.327 ($e^{0.283} \approx 1.327$). This indicates that, holding other variables constant, offering a bounty award increases the expected number of answers by a factor of 1.327 (or 32.7 %) compared with questions without bounties. For problem-solving likelihood ($Solved_i$), the odds ratio is 1.150 ($e^{0.140} \approx 1.150$). This indicates that, holding other variables constant, the odds of accepting a best answer for bountied questions are 1.150 times higher than for non-bountied questions. Additionally, as shown in Columns (3) and (4) of Table 4, the average quality of answers increases significantly when knowledge seekers offer a bounty award. The coefficients of $Bounty_i$ related to average score and textual relevance across all answers to a given question i are all positive and significant at the 0.01 level. This suggests that answers to questions with bounties are of higher quality than answers to those without bounties. Collectively, these findings support H1(a), H1(b), and H1(c), suggesting that when knowledge seekers set bounties on their questions, there is an increase in the number of answers, the likelihood of solving problems, and the average quality of answers.

5.2. The effect of bounty amount on content contribution

Table 5 presents estimation results using $Amount_i$ as the independent variable. As seen in Column (1), the coefficient of $Amount_i$ related to $Answers_i$ is significantly positive, and the coefficient of the quadratic term ($Amount_i^2$) related to $Answers_i$ is significantly negative. Column (2) shows a significant positive correlation between $Amount_i$ and $Solved_i$ and a significant negative correlation between $Amount_i^2$ and $Solved_i$. According to a prior study [43], we employed a three-step procedure to examine the inverted U-shaped effect of bounty amount on the likelihood of problem-solving. The key results indicate that the slope is steep, and the turning point of $Amount_i$ falls well within the range of observed values. Specifically, the test for a positive slope yields a t-value of 2.330 and a p-value of 0.010 (one-sided test), confirming the existence of an inverted U-shaped relationship between bounty amount and solving likelihood. These results indicate that H2(c) is supported. Regarding the relationship between $Amount_i$ and $Answers_i$, while both the linear and quadratic terms are statistically significant, the U test fails to reject the null hypothesis. This suggests that while a nonlinear relationship exists,

Table 2
Description of main variables in the cross-sectional dataset.

Variable	Description	Observations	Mean	S.D.	Min	Max
Dependent variables						
$Solved_i$	An indicator that equals 1 if a best answer is accepted for question i (and 0 otherwise)	119,990	0.465	0.499	0.000	1.000
$Answers_i$	The number of answers to question i	119,990	1. 535	0.900	1.000	6.000
$Score_i$	The average score (upvotes minus downvotes) across all answers received by question i	119,990	1.029	3.635	−12.000	342.000
$Relevance_i$	The average textual relevance between question i and its associated answers	119,990	0.096	0.075	0.000	0.684
Independent variables						
$Bounty_i$	An indicator that equals 1 if the knowledge seeker offers a bounty on question i (and 0 otherwise)	119,990	0.146	0.353	0.000	1.000
$Amount_i$	The bounty amount offered for question i (scaled by 1/100)	17,551[9]	0.980	0.985	0.500	5.000
Control variables						
$TitleLength_i$	The title length of question i	119,990	61.530	22.560	23.000	130.000
$BodyLength_i$	The number of words in the body of question i	119,990	344.300	458.100	25.000	2,757.000
$Tags_i$	The number of tags of question i	119,990	4.229	1.243	2.000	6.000
$FirstAnswer_i$	The number of days between the creation of question i and the receipt of its first answer	119,990	12.870	43.140	1.000	304.000
$ExistingAnswers_i$	The number of existing answers received for question i before the start of the bounty period	119,990	0.275	0.573	0.000	3.000
$Before_i$	An indicator that equals 1 if the knowledge seeker of question i had previously posted a bountied question (and 0 otherwise)	119,990	0.836	0.371	0.000	1.000
$UserDays_i$	The number of days between the knowledge seeker's registration and the creation of question i	119,990	3,005.469	1,192.687	1,069.000	6,001.000
$Reputation_i$	The knowledge seeker's reputation before the creation of question i	119,990	2,024.172	11,760.370	1.000	944,931.000
$Upvotes_i$	The number of upvotes received by the knowledge seeker before the creation of question i	119,990	224.018	809.747	0.000	37,203.000
$ExistingBounty_i$	The number of bountied questions posted by the knowledge seeker before the creation of question i	119,990	0.218	1.818	0.000	74.000
$Topic_i$	A categorical variable represents the extracted topic of question i using the latent Dirichlet allocation (LDA) model	119,990	3.548	2.421	0.000	7.000

[9] We observe 17,551 bountied questions ($Bounty_i = 1$); $Amount_i$ is recorded only for these observations.

Table 3
Description of main variables in the panel dataset.

Variable	Description	Observations	Mean	S.D.	Min	Max
Dependent variables						
$Solved_{i,t}$	An indicator that equals 1 if a best answer is accepted for question i on day t (and 0 otherwise)	100,803[10]	0.096	0.295	0.000	1.000
$Answers_{i,t}$	The number of answers to question i on day t	100,803	0.262	0.530	0.000	7.000
$Score_{i,t}$	The average score (upvotes minus downvotes) across all answers received by question i on day t	100,803	0.348	1.995	−6.000	426.000
$Relevance_{i,t}$	The average textual relevance score between question i and its associated answers on day t	100,803	0.015	0.043	0.000	0.514
Independent variable						
$Scarcity_{i,t}$	The number of days elapsed since the bounty was created	100,803	3.749	1.986	1.000	7.000
Control variables						
$Answers_{i,t-1}$	The number of answers to question i on day t-1	100,803	0.222	0.491	0.000	7.000
$Comment_{i,t}$	The number of comments to question i on day t	100,803	2.922	3.304	0.000	13.000
$Upvotes_{i,t}$	The number of upvotes to question i on day t	100,803	0.326	0.738	0.000	11.000

[10] The unbalanced panel contains 100,803 observations, covering 17,551 bountied questions with varying bounty durations.

it does not follow an inverted U-shape. The calculated turning point is 5.337, exceeding the upper bound of 5. Therefore, although the inverted U-shaped pattern is not supported, the effect of bounty amount on the number of answers exhibits an initial increase followed by stabilization, suggesting partial support for H2(a).

This is because opportunistic contributors may submit answers that imitate others at a lower cost in pursuit of higher rewards, resulting in a continuous increase in the number of answers as the bounty amount rises. However, the increase in low-quality answers does not necessarily correspond to a higher likelihood of the knowledge seeker receiving the best answer. Since the motivation of genuine contributors is still influenced by the difficulty level of the question, they tend to exert effort that matches the complexity of the problem when it falls within a certain range. Nevertheless, beyond a certain threshold, contributors may reduce their effort due to perceived difficulty surpassing their capabilities, resulting in an inverted U-shaped curve. In other words, increasing the bounty amount may indeed attract a larger number of individuals to answer a question on the surface, but it does not necessarily guarantee a higher likelihood of problem-solving. It may even decrease the chances of problem resolution. Hence, it is necessary for knowledge seekers to set an appropriate amount.

Interestingly, our empirical analysis reveals varying effects across the two quality measures, as shown in Columns (3–5) of Table 5. Specifically, the coefficient of $Amount_i$ on $Score_i$ (0.028, $p < 0.01$) is positively significant, while the coefficient of $Amount_i^2$ on $Score_i$ (–0.004, $p < 0.01$) is significantly negative. Following the three-step procedure, we confirm the presence of an inverted U-shaped relationship between the bounty amount and the answer score. For $Relevance_i$, the coefficient of $Amount_i$ (0.030, $p > 0.1$) and the coefficient of $Amount_i^2$ (–0.001, $p > 0.1$) are both nonsignificant. However, in an alternative regression excluding the quadratic term (shown in Column 4), we find that the coefficient of $Amount_i$ is 0.024 ($p < 0.01$). Thus, instead of an inverted U-shaped relationship, we observe a positive linear relationship. Given that these two measures capture different aspects of answer quality, it is reasonable that the bounty amount exhibits distinct effects across them. This is because the answer score reflects the overall quality of a response, encompassing factors such as content depth, clarity of expression, and originality. A higher bounty amount increases the perceived task value,

Table 4
Effects of offering bounty awards on content contribution.

Variable	(1) $Answers_i$	(2) $Solved_i$	(3) $Score_i$	(4) $Relevance_i$
$Bounty_i$	0.283***	0.140***	0.053***	0.108***
	(0.005)	(0.020)	(0.001)	(0.009)
$TitleLength_i$	0.000***	0.001*	0.000***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
$BodyLength_i$	−0.000	0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Tags_i$	0.005***	0.036***	0.003***	−0.005**
	(0.001)	(0.005)	(0.000)	(0.003)
$FirstAnswer_i$	0.003***	−0.003***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$ExistingAnswers_i$	0.514***	−0.387***	0.003***	−0.042***
	(0.002)	(0.011)	(0.001)	(0.005)
$Before_i$	0.010**	0.237***	0.010***	0.040***
	(0.005)	(0.022)	(0.002)	(0.011)
$UserDays_i$	−0.035***	−0.336***	−0.024***	0.018*
	(0.004)	(0.020)	(0.001)	(0.010)
$Reputation_i$	0.024***	0.053***	0.013***	0.021***
	(0.001)	(0.005)	(0.000)	(0.003)
$Upvotes_i$	−0.012***	0.181***	−0.000	−0.000
	(0.001)	(0.005)	(0.000)	(0.003)
$ExistingBounty_i$	0.012**	0.106***	−0.001	0.019**
	(0.006)	(0.022)	(0.001)	(0.009)
$Topic_i$	0.003***	−0.010***	0.002***	0.018***
	(0.000)	(0.002)	(0.000)	(0.001)
Constant	0.362***	1.667***	2.710***	−3.014***
	(0.033)	(0.165)	(0.010)	(0.080)
Log-likelihood	−147,162.700	−78,863.407	NA	167,726.340
Observations	119,990	119,990	119,990	119,990
Adj. R^2	0.089	0.048	0.097	0.022

Note: Robust standard errors are in parentheses.
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

motivating contributors to invest greater effort, refine their answer structure, and incorporate more supporting evidence to enhance their score. However, once the bounty amount surpasses a certain threshold, the associated increase in task difficulty may lead contributors to feel incapable of meeting expectations. Concerned about expending significant effort with little chance of success, some contributors may adopt opportunistic strategies, such as submitting responses that appear detailed but lack true depth, ultimately resulting in a decline in answer scores.

For answer relevance, this metric assesses textual similarity between the question and the answer, which may not fully align with the depth, accuracy, or utility of the answer. As the bounty amount increases, contributors are likely to ensure basic relevance when crafting thoughtful answers. However, even when the bounty amount reaches a critical threshold and contributors perceive a task as overly difficult, they are unlikely to submit irrelevant answers.

Fig. 2 visualizes the effect of bounty amount on content contribution, corresponding to Hypothesis 2. The upper panels display the patterns for quantity and problem-solving: a distinct inverted U-shaped curve is observed for problem-solving likelihood (H2c), while the relationship for answer quantity (H2a) does not exhibit a turning point within the observed range. The lower panels illustrate the effects on answer quality, as examined in H2(b). Specifically, H2(b) is partially supported: An inverted U-shaped relationship is observed between bounty amount and answer score, whereas only a linear relationship is found for textual relevance.

5.3. The effect of temporal scarcity on content contribution

The results presented in Table 6 correspond to Model (3). Our analysis reveals a notable pattern regarding temporal scarcity. First, we observe a negative coefficient of $Scarcity_{i,t}$ on $Answers_{i,t}$ (–1.213, $p <$ 0.01) and a significant positive coefficient of $Scarcity^2_{i,t}$ on $Answers_{i,t}$ (0.147, $p < 0.01$). Using the three-step procedure for the U test, we find that the two-sided slopes have opposite signs ($p < 0.01$), and the turning point lies within the 95 % confidence interval. This suggests a U-shaped relationship between temporal scarcity and the quantity of content contribution. In the model, we also include the number of answers to question i on the previous day ($Answers_{i,t-1}$) as a control. This variable partially accounts for potential social learning effects, as contributors may observe and respond to prior answers, allowing us to better isolate the impact of temporal scarcity on subsequent contributions. To elaborate on the practical significance of this U-shaped pattern, we calculated the turning point (4.113, $p < 0.01$) related to $Answers_{i,t}$, and it falls within the range of our dataset. That is, questions with extremely low or high temporal scarcity (i.e., at the beginning and the end of a bounty period) can receive more answers, in support of H3(a). In other words, when bounty tasks have ample time, contributors can allocate sufficient cognitive resources, which encourages more participation and results in a higher volume of answers. However, as the deadline approaches and available time decreases, participation drops, leading to fewer responses. When time becomes extremely scarce, the heightened sense of urgency may either discourage contributors from completing the task or prompt a surge in answer submissions as the deadline nears. At the same time, a deadline associated with the potential of a bounty award strengthens the effect of urgency.

Column (2) shows a negative coefficient of $Scarcity_{i,t}$ on $Solved_{i,t}$ (–1.207, $p < 0.01$) and a significant positive coefficient of $Scarcity^2_{i,t}$ on $Solved_{i,t}$ (0.127, $p < 0.01$). The results of the three-step procedure for the U test suggest that the two-sided slopes have opposite signs ($p < 0.01$), and the turning point lies within the 95 % confidence interval. The turning point is 4.571, and it falls within the range of our dataset. This suggests a U-shaped relationship between temporal scarcity and the likelihood of problem-solving. That is, questions with extremely low or high temporal scarcity (i.e., at the beginning and the end of a bounty period) are more likely to be solved, in support of H3(c).

As shown in Columns (3) and (4), we observe a significant negative correlation between $Scarcity_{i,t}$ and answer quality (–0.006, $p < 0.01$, DV = $Score_{i,t}$; -0.187, $p < 0.01$, DV = $Relevance_{i,t}$), while $Scarcity^2_{i,t}$ exhibits a significant positive correlation with these dependent variables (0.000, $p < 0.01$, DV = $Score_{i,t}$; 0.013, $p < 0.01$, DV = $Relevance_{i,t}$). However, the three-step U test indicates that the U-shaped pattern is not fully supported, as the estimated turning point (7.010, DV = $Score_{i,t}$; 7.317, DV = $Relevance_{i,t}$) lies outside the observed range of the independent variable (0–7). Thus, H3(b) is partially supported. This suggests that answer quality declines as temporal scarcity increases, but the downward trend weakens and eventually stabilizes rather than reversing. For average answer quality, bountied questions initially attract significant attention from participants, motivating them to invest greater effort in crafting more professional, informative, and valuable responses, resulting in answers that are more helpful and highly relevant. This trend naturally diminishes and eventually stabilizes over time. As time progresses, and particularly when the deadline becomes salient, contributors appear to shift toward a more strategic participation mode, prioritizing timely submission over content refinement. Importantly, although the number of submissions increases toward the end of the bounty window, this surge in participation does not result in further deterioration of answer quality. In other words, while quality does not rebound, it also does not decline further, indicating a plateau effect under high temporal scarcity.

The patterns in Fig. 3 reveal that temporal scarcity exhibits a consistent U-shaped relationship with the number of answers (i.e., H3a) and the likelihood of problem-solving (i.e., H3c), while the pattern for average answer quality (i.e., H3b) is partially supported.

Table 5
Effects of bounty amount on content contribution.

Variable	(1) $Answers_i$	(2) $Solved_i$	(3) $Score_i$	(4) $Relevance_i$	(5) $Relevance_i$
$Amount_i$	0.095***	0.180***	0.028***	0.024***	0.030
	(0.015)	(0.058)	(0.004)	(0.007)	(0.025)
$Amount_i^2$	−0.009***	−0.033***	−0.004***		−0.001
	(0.003)	(0.012)	(0.001)		(0.005)
$TitleLength_i$	−0.000	−0.001	−0.000*	0.007***	0.007***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
$BodyLength_i$	−0.000	0.000***	−0.000	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Tags_i$	0.013***	−0.025*	0.005***	−0.003	−0.003
	(0.003)	(0.013)	(0.001)	(0.006)	(0.006)
$FirstAnswer_i$	0.001***	−0.004***	0.000***	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ExistingAnswers_i$	0.424***	−0.281***	−0.000	−0.004	−0.004
	(0.004)	(0.030)	(0.002)	(0.013)	(0.013)
$Before_i$	0.012	0.050	0.012***	0.068***	0.068***
	(0.010)	(0.040)	(0.003)	(0.018)	(0.018)
$UserDays_i$	−0.040***	−0.462***	−0.028***	0.024	0.024
	(0.014)	(0.054)	(0.004)	(0.025)	(0.025)
$Reputation_i$	0.013***	−0.086***	0.006***	0.019***	0.019***
	(0.004)	(0.015)	(0.001)	(0.007)	(0.007)
$Upvotes_i$	−0.004	0.217***	0.006***	0.010	0.010
	(0.003)	(0.013)	(0.001)	(0.006)	(0.006)
$ExistingBounty_i$	0.011*	0.122***	−0.00*	0.017	0.017
	(0.007)	(0.027)	(0.002)	(0.011)	(0.011)
$Topic_i$	−0.010***	−0.031***	0.001	0.011***	0.011***
	(0.002)	(0.007)	(0.000)	(0.003)	(0.003)
Constant	0.679***	3.833***	2.798***	−3.132***	−3.132***
	(0.107)	(0.429)	(0.029)	(0.194)	(0.194)
Log-likelihood	−25,641.319	−11,528.037	NA	25,266.474	25,266.517
Observations	17,551	17,551	17,551	17,551	17,551
Adj. R^2	0.062	0.033	0.028	0.846	0.846

Note: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$,
* $p < 0.1$.

6. Robustness checks and discussions

6.1. Matching

6.1.1. Coarsened exact matching

Given the potential systematic differences between questions with and without bounty awards, as well as the need to improve sample balance, we employ a coarsened exact matching (CEM) [64] method to address concerns related to heterogeneity between the treatment and control groups. In contrast to propensity score matching, which reduces multidimensional vectors to a single dimension, CEM allows the exact matching of groups based on multiple attributes. CEM coarsens the observations into strata based on covariates, retaining only the strata that contain both treatment and control observations, thereby limiting the matched data to common support areas [65].

We match the samples of non-bountied questions and bountied questions using six covariates, which are shown in Table 7. The imbalance statistics (L1 distance) decrease, indicating that the imbalance measure for each variable improved after coarsened exact matching. We use the matched sample to fit Model (1). The results, presented in Table 8, continue to support H1.

6.1.2. Propensity score matching

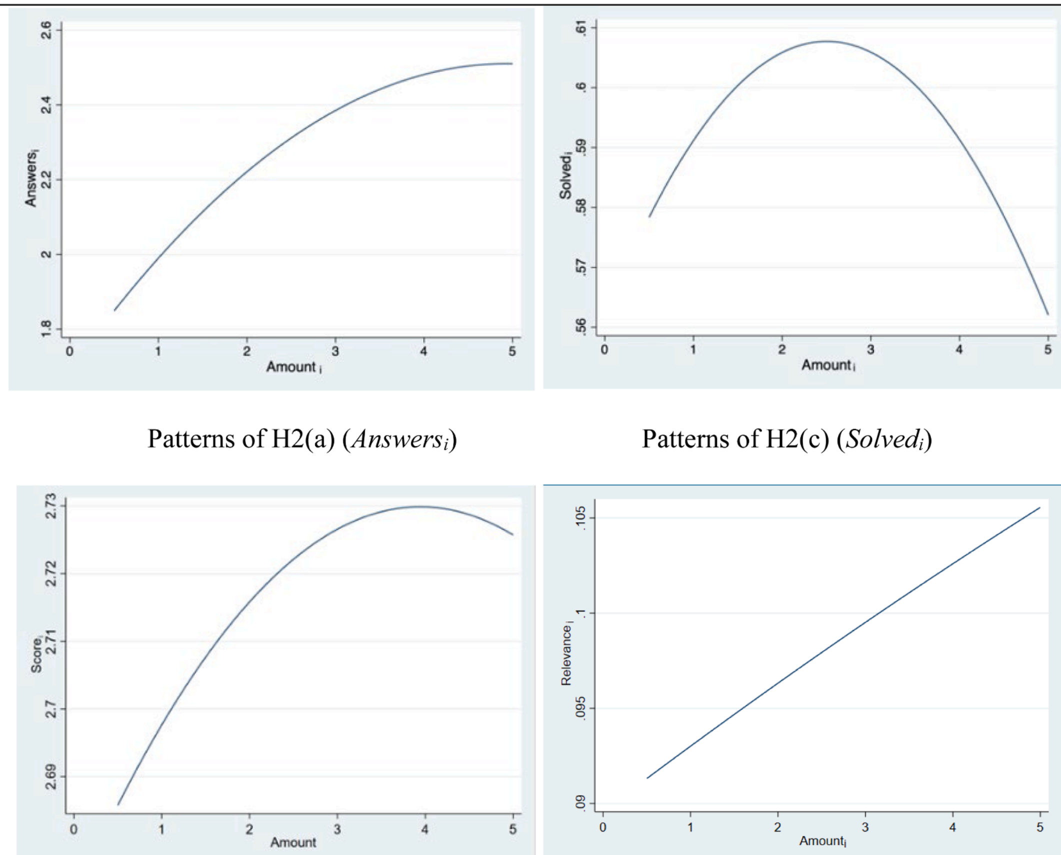
As a robustness check, we also employ an alternative matching method, propensity score matching (PSM), to validate the results. This approach mitigates the endogeneity problem by matching questions with and without bounties based on both question-level and seeker-level characteristics, using the same covariates as in the CEM method. Our matched sample shows no significant differences post-matching and satisfies the balancing property. As shown in Table 9, the results are consistent with the main analysis, confirming the robustness of our study.

6.2. Instrumental variable method

While this study employs both CEM and PSM to address potential selection bias, the current model identification strategy may still be subject to endogeneity concerns. To strengthen causal inference, we employ an instrumental variable approach. A valid instrument for our endogenous variable, $Bounty_i$, must satisfy two conditions. First, it must be sufficiently correlated with the endogenous variable, meaning it should affect $Bounty_i$ significantly. Second, it must satisfy the exclusion restriction: it should influence the quantity and quality of contribution solely through its effect on $Bounty_i$.

In this context, we identify a seeker-level variable, knowledge seekers' reputation (denoted as $SeekerReputation_i$), as a potential instrument. Specifically, knowledge seekers with higher reputations are more likely to offer a bounty award, as they may adopt a less cautious approach when deciding whether to do so and the amount to set. This instrument variable is unlikely to directly affect contributors' behavior or motivations through channels other than the bounty itself, thereby satisfying the exogeneity requirement. Thus, we consider this variable valid for our analysis.

We apply a two-stage least squares (2SLS) method. The first-stage Kleibergen–Paap Wald F statistic for $Bounty_i$ is 105.93, exceeding the critical value and indicating that our instrument is sufficiently strong [66]. The results of the IV regression are presented in Table 10. The findings for all four dependent variables remain consistent with the main effects, confirming the robustness of our results.



Patterns of H2(a) (*Answers$_i$*)

Patterns of H2(c) (*Solved$_i$*)

Patterns of H2(b) (*Score$_i$*)

Patterns of H2(b) (*Relevance$_i$*)

Fig. 2. Patterns of H2.

Table 6
Effects of temporal scarcity on content contribution.

Variable	(1) *Answers$_{i,t}$*	(2) *Solved$_{i,t}$*	(3) *Score$_{i,t}$*	(4) *Relevance$_{i,t}$*
Scarcity$_{i,t}$	−1.213***	−1.207***	−0.006***	−0.187***
	(0.039)	(0.079)	(0.000)	(0.003)
Scarcity$^2_{i,t}$	0.147***	0.127***	0.000***	0.013***
	(0.005)	(0.010)	(0.000)	(0.000)
Answers$_{i,t-1}$	−0.213***	−0.516***	−0.001***	−0.046***
	(0.015)	(0.030)	(0.000)	(0.004)
Comment$_{i,t}$	1.915***	3.243***	0.048***	2.403***
	(0.019)	(0.049)	(0.002)	(0.028)
Upvotes$_{i,t}$	0.172***	0.205***	0.001***	0.038***
	(0.007)	(0.016)	(0.000)	(0.003)
Constant	7.596***	−0.272***	1.966***	−3.910***
	(1.111)	(0.080)	(0.001)	(0.015)
Time fixed effect	Yes	Yes	Yes	Yes
Question fixed effect	Yes	Yes	Yes	Yes
Topic fixed effect	Yes	Yes	Yes	Yes
Log-likelihood	−55,568.337	−26,347.945	NA	544,925.470
Observations	100,803	100,803	100,803	100,803
Adj. R^2	0.138	0.170	0.085	0.098

Note: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

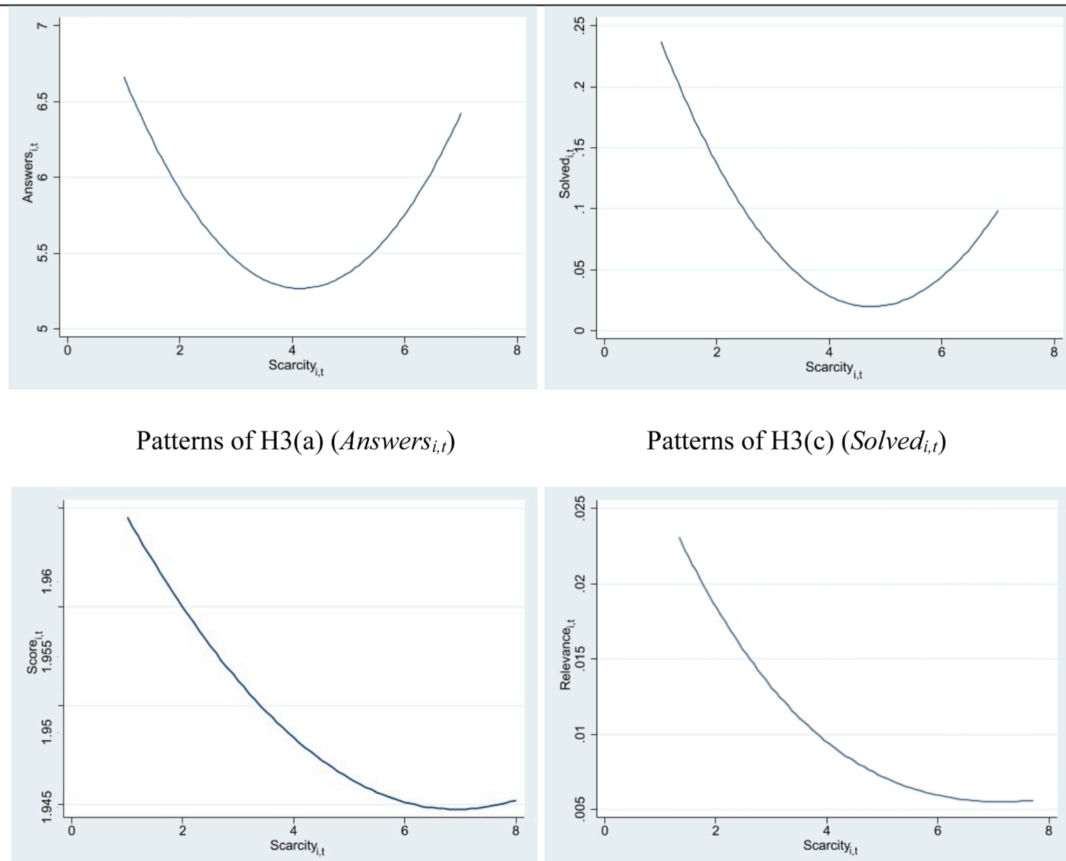
6.3. Heterogeneity analyses

Since the number of answers reflects the level of contributor engagement, and the likelihood of problem-solving captures whether the question received a satisfactory resolution from the knowledge seeker's perspective, we consider these two variables as the most essential outcomes in the knowledge-sharing context. Therefore, our heterogeneity analyses primarily focus on them.

6.3.1. The role of question quality

Given that the quality of bountied questions may influence potential contributors' perceptions of the required cognitive resources and their attention allocation, we include question quality as a moderator to gain additional insights into the boundary conditions of the bounty award's effects. Prior studies [21,64] have proposed a method to measure post quality that addresses the common confounding between quality and popularity: specifically, the tendency for frequently viewed questions to receive more votes regardless of content quality. Drawing on both theoretical reasoning and empirical evidence, they define question quality as *QueQuality$_i$* $= s_i / v_i$, where s_i is the score of question i and v_i is the number of views. Here, the view count serves as a control for popularity. We adopt this measure in our analysis, where a higher value of *QueQuality$_i$* indicates a higher-quality question. To test the moderating role of question quality, we include interaction terms between *QueQuality$_i$* and key independent variables in Model (2) and Model (3).

As shown in Columns (1) and (2) of Table 11, the coefficients of *QueQuality$_i$* × *Amount^2_i* regarding *Answers$_i$* and *Solved$_i$* are –0.604 ($p < 0.1$) and 1.188 ($p > 0.1$), respectively. These findings suggest a moderating effect of question quality on the inverted U-shaped relationship between *Amount$_i$* and the number of answers received, but not on the relationship between *Amount$_i$* and the likelihood of problem-solving. Therefore, as question quality increases, a steeper inverted U-



Patterns of H3(a) ($Answers_{i,t}$) Patterns of H3(c) ($Solved_{i,t}$)

Patterns of H3(b) ($Score_{i,t}$) Patterns of H3(b) ($Relevance_{i,t}$)

Fig. 3. Patterns of H3.

Table 7
The multivariate imbalance statistics of coarsened exact matching.

	Treatment Group and Control Group			
	Before		After	
	Difference	L1	Difference	L1
$TitleLength_i$	1.260	0.046	0.002	0.027
$BodyLength_i$	120.110	0.163	4.813	0.057
$Tags_i$	0.305	0.102	−0.000	0.000
$FirstAnswer_i$	9.751	0.301	1.755	0.238
$ExistingAnswers_i$	−0.089	0.088	−0.000	0.000
$Before_i$	−0.499	0.499	−0.000	0.000
Multivariate L1		0.832		0.830

shaped relationship emerges, signifying an enhancement in the sensitivity of content contribution quantity to bounty amount for high-quality questions. In simpler terms, when dealing with high-quality questions, contributors tend to be more responsive to changes in the bounty amount. This phenomenon may be attributed to the fact that high-quality questions tend to be more appealing, attracting more competition and the perception of a higher reward value, all of which collectively amplify the impact of the bounty amount.

In Columns (3) and (4) of Table 11, the coefficients of the interaction terms between question quality ($QueQuality_i$) and temporal scarcity ($Scarcity_{i,t}$ and $Scarcity^2_{i,t}$) are statistically nonsignificant for both the number of answers ($Answers_{i,t}$) and the likelihood of problem-solving ($Solved_{i,t}$). In other words, we find no evidence that higher-quality questions systematically alter how contributors respond to changes in the remaining bounty time. One possible explanation is that generating high-quality answers or ultimately solving a problem requires substantial expertise and effort, which are less sensitive to temporal scarcity.

6.3.2. The role of answer inadequacy

Following the work of Su et al. (2023) [67], which suggests that answer inadequacy affects contributors' effort in knowledge contribution, we incorporate a dummy variable, $UnderAnswered_i$, to categorize questions based on their answer volume prior to offering the bounty award. A value of 1 indicates "under-answered" questions—those in the bottom 50 % in terms of answer count before the bounty was offered. A value of 0 indicates "well-answered" questions—those in the top 50 % of pre-bounty answer volume.

The results of this analysis, as shown in Columns (1) and (2) of Table 12, indicate that contributors are more responsive to the bounty amount when engaging with under-answered questions, leading to a higher sensitivity of answer volume to bounty amount ($\beta = -0.023, p < 0.01$). However, the effect of the bounty amount on the likelihood of receiving the best answer is not moderated by the level of answer inadequacy. This may be because, for under-answered questions, contributors are primarily motivated by the bounty amount to invest their effort in filling the gaps in responses, but the answers they provide may not necessarily help the knowledge seeker solve the problem. The results in Columns (3) and (4) show that there are no moderating effects of $UnderAnswered_i$ on the relationship between temporal scarcity and content contribution. One possible reason is that the measure of $UnderAnswered_i$ is based on the number of answers available at the time the bounty was offered. As temporal scarcity progresses, the answer

Table 8
Effects of offering bounty awards on content contribution using the CEM sample.

Variable	(1) $Answers_i$	(2) $Solved_i$	(3) $Score_i$	(4) $Relevance_i$
$Bounty_i$	0.308***	0.231***	0.057***	0.120***
	(0.006)	(0.019)	(0.002)	(0.012)
$TitleLength_i$	−0.000	0.002***	0.000**	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
$BodyLength_i$	−0.000***	0.000***	−0.000**	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Tags_i$	0.001	0.020***	0.003***	0.002
	(0.002)	(0.005)	(0.001)	(0.007)
$FirstAnswer_i$	0.003***	−0.003***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$ExistingAnswers_i$	0.538***	−0.434***	0.009***	−0.047***
	(0.004)	(0.015)	(0.003)	(0.016)
$Before_i$	0.059***	0.035*	0.009***	0.050***
	(0.008)	(0.019)	(0.002)	(0.019)
$UserDays_i$	−0.036***	−0.183***	−0.022***	0.030
	(0.010)	(0.023)	(0.003)	(0.025)
$Reputation_i$	0.014***	−0.029***	0.009***	0.018**
	(0.003)	(0.006)	(0.001)	(0.007)
$Upvotes_i$	−0.004*	0.197***	0.002***	0.004
	(0.002)	(0.005)	(0.001)	(0.007)
$ExistingBounty_i$	0.000	0.019	−0.001	0.009
	(0.006)	(0.016)	(0.002)	(0.022)
$Topic_i$	0.005***	−0.004	0.002***	0.019***
	(0.001)	(0.003)	(0.000)	(0.003)
Constant	0.327**	0.703***	2.706***	−3.125***
	(0.076)	(0.180)	(0.023)	(0.196)
Log-likelihood	−127,582.060	−70,537.688	NA	147,615.130
Observations	105,958	105,958	105,958	105,958
Adj. R^2	0.065	0.038	0.066	0.101

Note: Robust standard errors are in parentheses.
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

Table 9
Effects of offering bounty awards on content contribution using the PSM sample.

Variable	(1) $Answers_i$	(2) $Solved_i$	(3) $Score_i$	(4) $Relevance_i$
$Bounty_i$	0.282***	0.153***	0.053***	0.113***
	(0.005)	(0.020)	(0.001)	(0.009)
$TitleLength_i$	0.000***	−0.000	0.000***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
$BodyLength_i$	−0.000	0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Tags_i$	0.005***	0.025***	0.003***	−0.005
	(0.001)	(0.006)	(0.000)	(0.003)
$FirstAnswer_i$	0.003***	−0.003***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$ExistingAnswers_i$	0.506***	−0.385***	0.002**	−0.030***
	(0.003)	(0.016)	(0.001)	(0.008)
$Before_i$	0.012**	0.191***	0.009***	0.039***
	(0.006)	(0.024)	(0.002)	(0.012)
$UserDays_i$	−0.034***	−0.348***	−0.023***	0.023*
	(0.006)	(0.026)	(0.002)	(0.013)
$Reputation_i$	0.024***	0.023***	0.012***	0.019***
	(0.002)	(0.007)	(0.001)	(0.004)
$Upvotes_i$	−0.011***	0.192***	0.001***	0.004
	(0.002)	(0.006)	(0.000)	(0.003)
$ExistingBounty_i$	0.012**	0.102***	−0.002	0.018*
	(0.006)	(0.022)	(0.001)	(0.009)
$Topic_i$	0.002**	−0.009***	0.002***	0.018***
	(0.001)	(0.003)	(0.000)	(0.002)
Constant	0.283***	1.766***	2.704***	−3.080***
	(0.044)	(0.203)	(0.013)	(0.104)
Log-likelihood	−90,118.400	−47,769.072	NA	101,605.500
Observations	72,050	72,050	72,050	72,050
Adj. R^2	0.081	0.043	0.101	0.381

Note: Robust standard errors are in parentheses.
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

count may change, making the initial under-answered status less informative of contributors' later decisions. Consequently, contributors' responsiveness under deadline pressure is less likely to be systematically influenced by whether a question was initially under-answered.

6.3.3. The role of the contributor's reputation

Additionally, we consider contributor segments. Although the reputation system involves complex algorithms, it can partially reflect a contributor's ability to provide professional and valuable answers. According to previous research [68], more professional contributors tend to contribute higher-value answers. Therefore, we first calculated the average reputation of contributors who provided answers to each question *i*. Then we incorporated a dummy variable, $HighReputation_i$. A value of "1" indicates questions where the associated contributors are in the top 50 % of reputation (classified as high-reputation contributors). Conversely, a value of "0" indicates those in the bottom 50 % (classified as low-reputation contributors).

Column (3) of Table 13 shows that only the U-shaped relationship between $Scarcity_{i,t}$ and $Answers_{i,t}$ is moderated by $HighReputation_i$. The significant coefficient of the second-order interaction term (–0.146, $p < 0.01$) suggests that high-reputation contributors attenuate the quadratic effect of $Scarcity_{i,t}$, leading to a flatter U-shaped curve and potentially shifting the turning point to the left. Meanwhile, the significant coefficient of the first-order interaction term (0.740, $p < 0.01$) indicates that high-reputation contributors mitigate the negative linear effect of $Scarcity_{i,t}$, reducing its negative impact on $Answers_{i,t}$ at lower scarcity levels (i.e., the decline in answers is less pronounced). In other words, high-reputation contributors are less sensitive to temporal scarcity, likely due to their richer experience and stronger time management skills. As a result, even under high-scarcity conditions, they exhibit more stable engagement patterns compared to low-reputation contributors. In contrast, low-reputation contributors exhibit greater sensitivity to

Table 10
Results of Model (1) using instrumental variables.

Variable	(1) $Answers_i$	(2) $Solved_i$	(3) $Score_i$	(4) $Relevance_i$
$Bounty_i$	4.967***	1.615***	1.797***	0.169***
	(0.493)	(0.227)	(0.181)	(0.030)
$TitleLength_i$	0.001***	0.000**	0.000**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$BodyLength_i$	−0.000***	−0.000	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Tags_i$	−0.071***	−0.019***	−0.027***	−0.004***
	(0.009)	(0.004)	(0.003)	(0.001)
$FirstAnswer_i$	0.003***	−0.001***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$ExistingAnswers_i$	1.241***	−0.043***	0.052***	0.002
	(0.016)	(0.007)	(0.006)	(0.001)
$Before_i$	1.326***	0.522***	0.525***	0.053***
	(0.148)	(0.068)	(0.054)	(0.009)
$UserDays_i$	−0.044***	−0.076***	−0.023***	0.053***
	(0.016)	(0.006)	(0.005)	(0.009)
$Upvotes_i$	−0.084***	0.020***	−0.026***	−0.003***
	(0.010)	(0.005)	(0.004)	(0.001)
$ExistingBounty_i$	−0.768***	−0.259***	−0.314***	−0.030***
	(0.089)	(0.041)	(0.033)	(0.005)
$Topic_i$	0.021***	0.003***	0.008***	0.003***
	(0.002)	(0.001)	(0.001)	(0.000)
Constant	0.225	0.455***	2.304***	0.012
	(0.139)	(0.064)	(0.051)	(0.009)
Observations	119,990	119,990	119,990	119,990
Adj. R^2	0.322	0.017	0.958	0.455

Note: Robust standard errors are in parentheses.
*** $p < 0.01$,
** $p < 0.05$, *$p < 0.1$.

Table 11
The moderating effects of $QueQuality_i$.

Variable	(1) $DV = Answers_i$ $IV = Amount_i$	(2) $DV = Solved_i$ $IV = Amount_i$	(3) $DV = Answers_{i,t}$ $IV = Scarcity_{i,t}$	(4) $DV = Solved_{i,t}$ $IV = Scarcity_{i,t}$
IV	0.075***	0.245***	−1.049***	−1.192***
	(0.019)	(0.074)	(0.018)	(0.081)
IV^2	−0.005	−0.040***	0.128***	0.126***
	(0.004)	(0.015)	(0.002)	(0.011)
$QueQuality_i$	−5.271***	−4.454	−5.329**	−7.056*
	(1.046)	(4.171)	(2.220)	(4.164)
$QueQuality_i \times IV$	3.255**	−8.700	−0.219	−1.115
	(1.651)	(6.306)	(1.637)	(3.050)
$QueQuality_i \times IV^2$	−0.604*	1.188	−0.205	−0.053
	(0.340)	(1.331)	(0.210)	(0.399)
Control	Yes	Yes	Yes	Yes
Time fixed effect	No	No	Yes	Yes
Question fixed effect	No	No	Yes	Yes
Topic fixed effect	Yes	Yes	Yes	Yes
Constant	0.892***	3.851***	7.950***	−0.233***
	(0.113)	(0.453)	(1.606)	(0.085)
Log-likelihood	−25, 621.233	−11, 486.655	−55,485.727	−26,310.345
Observations	17,551	17,551	100,803	100,803

Note: Robust standard errors are in parentheses.
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

temporal scarcity. As the bounty deadline approaches, they are more likely to prioritize urgent tasks, which enhances their motivation to participate and increases the number of answers they provide.

7. Conclusions and implications

Bounty awards are widely adopted on knowledge-sharing platforms, yet their role in assisting knowledge seekers remains underexplored. Drawing on the literature of motivational intensity theory and temporal scarcity, we develop hypotheses regarding how the two key features of bounty awards, seeker-customized amounts and temporal dynamics, impact content contribution. To empirically test these hypotheses, we collected data from Stack Overflow and constructed both cross-sectional and unbalanced panel datasets. Our findings show that offering a bounty award significantly increases content contribution. Moreover, we observe an inverted U-shaped relationship between the bounty amount and two key outcomes: the likelihood of problem-solving and answer scores. For the number of answers, the effect of bounty amount follows a pattern of diminishing marginal returns, whereas for answer relevance, it exhibits a positive linear relationship with no evidence of an inverted U-shape. We also find that temporal scarcity has a U-shaped effect on content contribution—in terms of both quantity and the likelihood of problem-solving—while the U-shaped pattern in answer quality is only partially supported (i.e., it exhibits a convex decreasing trend that stabilizes over time). Additionally, several interesting heterogeneity effects have been identified. For example, high-quality questions amplify contributors' sensitivity to the bounty amount, thereby strengthening the effect on the number of answers. Answer inadequacy increases responsiveness to the bounty amount but does not alter sensitivity to temporal scarcity. Contributors' reputation affects their sensitivity to temporal scarcity, with low-reputation contributors exhibiting a stronger urgency-driven response.

Our study contributes to existing research in several important ways. First, we identify a novel incentive structure, bounty awards, which differs from traditional rule-based incentives by incorporating two distinctive features: seeker-customized reward amount and temporal dynamics. This innovation enriches the variety of incentive mechanisms and fills a theoretical gap in incentive design. Bounty awards can leverage the benefits of customized awards to dynamically encourage voluntary user contributions. Second, we advance the motivation literature by elucidating the unique mechanism of the bounty amount. As a reward feature, the seeker-customized reputational amount motivates contributors through a trade-off between perceived value and question difficulty, which helps explain the non-monotonic effects of bounty amount on contribution behaviors, deepening our understanding of how reward features influence individual motivation. Third, our study extends the literature on temporal scarcity—previously studied in the workplace, educational, and marketing contexts—into the domain of knowledge-sharing. Our findings shed light on how temporal constraints shape voluntary contribution behaviors, thus enriching motivation theory in digital environments.

In terms of practical implications, this study offers several actionable insights for practitioners. First, for all contributors, platforms can develop intelligent bounty recommendation systems that provide a global reference for bounty levels, ensuring that moderate-level rewards

Table 12
The moderating effects of $UnderAnswered_i$.

Variable	(1) $DV = Answers_i$ $IV = Amount_i$	(2) $DV = Solved_i$ $IV = Amount_i$	(3) $DV = Answers_{i,t}$ $IV = Scarcity_{i,t}$	(4) $DV = Solved_{i,t}$ $IV = Scarcity_{i,t}$
IV	−0.089***	0.038	−1.365***	−1.899***
	(0.017)	(0.190)	(0.073)	(0.132)
IV^2	0.013***	−0.018	0.161***	0.194***
	(0.003)	(0.038)	(0.009)	(0.017)
$UnderAnswered_i$	0.433***	−0.132	−0.040	−1.459***
	(0.015)	(0.143)	(0.090)	(0.157)
$UnderAnswered_i \times IV$	0.198***	0.152	−0.019	0.093
	(0.023)	(0.199)	(0.063)	(0.106)
$UnderAnswered_i \times IV^2$	−0.023***	−0.014	0.003	−0.002
	(0.005)	(0.040)	(0.007)	(0.015)
Control	Yes	Yes	Yes	Yes
Time fixed effect	No	No	Yes	Yes
Question fixed effect	No	No	Yes	Yes
Topic fixed effect	No	No	Yes	Yes
Constant	0.426***	3.938***	7.349***	1.115***
	(0.107)	(0.470)	(0.912)	(0.169)
Log-likelihood	−25,621.233	−11,486.655	−55,514.398	−26,290.620
Observations	17,551	17,551	100,803	100,803

Note: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13
The moderating effects of $HighReputation_i$.

Variable	(1) DV = $Answers_i$ IV= $Amount_i$	(2) DV =$Solved_i$ IV= $Amount_i$	(3) DV = $Answers_{i,t}$ IV= $Scarcity_{i,t}$	(4) DV =$Solved_{i,t}$ IV= $Scarcity_{i,t}$
IV	0.140***	−0.198	−0.919***	−0.005
	(0.037)	(0.141)	(0.042)	(0.088)
IV^2	−0.021***	0.012	0.169***	0.039***
	(0.008)	(0.032)	(0.005)	(0.011)
$HighReputation_i$	0.114***	0.409***	3.163***	4.608***
	(0.024)	(0.096)	(0.091)	(0.233)
$HighReputation_i \times IV$	−0.059	0.415***	0.740***	−0.040
	(0.040)	(0.154)	(0.050)	(0.192)
$HighReputation_i \times IV^2$	0.015*	−0.053	−0.146***	0.018
	(0.009)	(0.034)	(0.007)	(0.033)
Control	Yes	Yes	Yes	Yes
Time fixed effect	No	No	Yes	Yes
Question fixed effect	No	No	Yes	Yes
Topic fixed effect	No	No	Yes	Yes
Constant	0.788***	3.690***	6.215***	−4.384***
	(0.115)	(0.464)	(1.564)	(0.150)
Log-likelihood	−11,486.655	−15,934.650	−39,515.406	−19,113.573
Observations	17,551	17,551	100,803	100,803

Note: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$,
* $p < 0.1$.

effectively stimulate answer quantity, quality, and the likelihood of problem-solving. Second, given that temporal scarcity exerts a U-shaped effect on answer quantity and problem-solving likelihood, platforms can employ personalized task-ranking interfaces that incorporate each contributor's historical behavioral preferences, the remaining time for questions, and the bounty amount, thereby recommending the most motivating questions and guiding contributors to optimally schedule their responses to enhance overall engagement. Third, for high-quality or under-answered questions, platforms can use algorithms to offer bounty-setting recommendations to knowledge seekers, encouraging them to set slightly above-average rewards on these questions to more effectively attract contributor participation. Fourth, considering that low-reputation contributors are more sensitive to time pressure, platforms can send personalized reminders or notifications to these specific contributors, highlighting questions relevant to them as the bounty window approaches its end, further stimulating participation and thereby increasing overall answer volume.

Our study has several limitations that are worth noting. First, our analysis is based on observational data, and voluntary contribution activities might be captured more realistically in a field setting. Therefore, collaboration with online platforms could further validate the effectiveness of bounty awards. Second, our study is based on Stack Overflow, where questions are primarily technical and code-related. Whether our findings generalize to other knowledge-sharing contexts (e.g., healthcare, Q&A communities like Zhihu, or broader social platforms) remains to be validated, as user groups and problem types may differ substantially. Third, some hypothesized nonlinear relationships (e.g., U-shaped or inverted U-shaped effects) are not fully supported, possibly because the upper bound of the bounty amount in our dataset is limited. Future research could explore settings with higher or more flexible reward levels to examine whether the relationships hold beyond the observed range. Fourth, although multiple seeker- and question-level characteristics are controlled, unobserved heterogeneity may still exist. For instance, contributors' intrinsic motivations or unobservable personal characteristics are not directly captured in our data, which may influence contribution behaviors. Future research could integrate survey or experimental methods to address such unmeasured factors. Broadly, we hope that this study will inspire a new stream of research primarily focusing on information-oriented content and the tools available to platforms for shaping such content.

CRediT authorship contribution statement

Min Yu: Writing – original draft, Formal analysis, Data curation, Writing – review & editing, Methodology. **Mingyue Zhang:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Project administration. **Baojun Ma:** Writing – review & editing, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no competing interests.

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Appendix. Supplementary Analysis: Answer Length as a Proxy for Contributor Effort

Our main analyses in Section 5 focus on three key outcome dimensions: answer quantity, the likelihood of problem-solving, and average answer quality. Among these, the first two reflect question-level outcomes—capturing overall response volume and resolution success—while the third represents an individual-level outcome, reflecting the average quality of content generated by contributors. To further capture individual contributors' behavioral responses to bounty incentives, we examine their effort investment, which is not directly observable but can be approximated by answer length. Answer length serves as a mixed indicator of contributor effort in prior literature, reflecting both contribution level (e.g., Zhang et al. [69]) and content quality (e.g., Cao et al. [63]). Following established research [70,71], we treat this as a meaningful proxy for cognitive and temporal effort investment in content production.

In light of this, we include answer length as a supplementary outcome to assess the effects of bounty mechanisms—such as the presence of a bounty, its amount, and temporal scarcity. Specifically, offering a bounty award may increase perceived task value, thereby motivating greater effort allocation. At the question level, we compute the average length ($Length_i$) across all answers received for question *i*. The variable related to length is log-transformed to normalize its distribution, so we employ linear regression models.

Table A.1 presents estimation results using $Bounty_i$ and $Amount_i$ as independent variables. As seen in Column (1), the coefficient of $Bounty_i$ is significantly positive (0.500, $p < 0.01$). This suggests that answers to questions with bounties are longer than those to questions without bounties. In Column (3), the coefficient of $Amount_i$ is significantly positive (0.224, $p < 0.01$), and the coefficient of the quadratic term ($Amount_i^2$) is significantly negative (–0.025, $p < 0.01$). Following the U test procedure, we confirm that the inverted U-shaped relationship is not statistically significant ($p = 0.151$). This suggests that the effect of bounty amount on answer length exhibits diminishing marginal returns: While higher bounties initially motivate greater effort, the effect stabilizes at higher amounts without forming a true turning point.

Table A.1
Effects of offering bounty awards and bounty amount on contributor effort.

Dependent Variable	(1) $Length_i$	(2) $Length_i$	(3) $Length_i$
$Bounty_i$	0.500***		
	(0.008)		
$Amount_i$		0.104***	0.224***
		(0.007)	(0.024)
$Amount_i^2$			−0.025***
			(0.006)
$TitleLength_i$	0.000***	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
$BodyLength_i$	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
$Tags_i$	0.031***	0.037***	0.036***
	(0.002)	(0.005)	(0.005)
$FirstAnswer_i$	−0.001***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)
$ExistingAnswers_i$	0.046***	0.023*	0.021*
	(0.005)	(0.012)	(0.012)
$Before_i$	0.021**	0.021	0.028*
	(0.010)	(0.016)	(0.016)
$UserDays_i$	−0.013	−0.087***	−0.093***
	(0.009)	(0.022)	(0.022)
$Reputation_i$	0.021***	0.007	0.006
	(0.002)	(0.006)	(0.006)
$Upvotes_i$	0.013***	0.023***	0.023***
	(0.002)	(0.005)	(0.005)
$ExistingBounty_i$	0.002	0.003	0.004
	(0.009)	(0.011)	(0.011)
$Topic_i$	−0.022***	−0.027***	−0.027***
	(0.001)	(0.003)	(0.003)
Constant	6.314***	7.430***	7.410***
	(0.070)	(0.174)	(0.174)
Observations	119,990	17,551	17,551
Adj. R^2	0.077	0.047	0.048

Note: Robust standard errors are in parentheses.
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

Table A.2 presents estimation results using $Scarcity_{i,t}$ as an independent variable. The results demonstrate that answer length exhibits a non-linear response to temporal scarcity: While decreasing linearly with $Scarcity_{i,t}$ (–0.838, $p < 0.01$ in Column 2), it shows a positive quadratic relationship (0.062, $p < 0.01$ in Column 2). Formal U test analysis confirms that the U-shaped relationship is not statistically significant ($p = 0.415$), indicating that the effect reaches a plateau rather than a reversal. Contributors appear to write longer answers when more time is available, but tend to limit additional effort as deadlines approach—likely prioritizing speed over depth under time pressure.

Compared with other outcome indicators, such as answer quality or quantity, answer length reflects contributors' input effort rather than output value or competitive success. Thus, while bounty amount motivates contributors to write more detailed responses, temporal scarcity constrains such effort; yet in both cases, the effects stabilize, leading to a plateau rather than a reversal.

Table A.2
Effects of temporal scarcity on contributor effort.

Variable	(1) $Length_{i,t}$	(2) $Length_{i,t}$
$Scarcity_{i,t}$	−0.346***	−0.838***
	(0.005)	(0.013)
$Scarcity_{i,t}^2$		0.062***
		(0.001)
$Answers_{i,t-1}$	−0.551***	−0.551***
	(0.014)	(0.014)
$Comment_{i,t}$	9.294***	9.294***
	(0.074)	(0.074)
$Upvotes_{i,t}$	0.128***	0.128***
	(0.009)	(0.009)
Constant	2.473***	2.904***
	(0.028)	(0.035)
Time fixed effect	Yes	Yes

(*continued on next page*)

Table A.2 (*continued*)

Variable	(1) $Length_{i,t}$	(2) $Length_{i,t}$
Question fixed effect	Yes	Yes
Topic fixed effect	Yes	Yes
Observations	100,803	100,803
Adj. R^2	0.458	0.458

Note: Robust standard errors are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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