Rejection Design for Crowdsourcing Platforms

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Crowdsourcing is a powerful tool for harnessing collective intelligence, but it faces challenges due to variability in participant effort and submission quality. To mitigate this, some platforms have empowered requesters by enabling them to reject unsatisfactory submissions and obtain full refunds. However, the optimal use of such rejection designs remains underexplored. This paper establishes the efficiency and near-optimality of the rejection design using an auction framework. We show that the rejection design incentivizes higher-quality contributions from more capable crowdworkers and, in large-scale tasks, closely approximates the theoretical best outcome under full information. Next, we examine the equilibrium between a platform and a requester. Our analysis reveals a counterintuitive finding: adopting the rejection design creates a tripartite win-win-win situation for the platform, the requester, and the crowdworkers. Additionally, we demonstrate that the common industry practice of imposing a minimum acceptance rate with full refunds is suboptimal. Instead, our proposed design, which charges a fee for rejections without enforcing acceptance thresholds, better aligns incentives and effectively coordinates the system as if the platform and requester were a single decision-maker. Based on these findings, we recommend platforms to adopt fee-based rejection strategies to enhance performance and promote sustainable crowdsourcing ecosystems.

Key words: Crowdsourcing, Platform Design, Quality Control, Rejection Design, Pricing Strategy, Auction

1. Introduction

Crowdsourcing has emerged as a powerful tool for leveraging the collective intelligence of a diverse audience across various fields (Boudreau and Lakhani 2013). A compelling example is NASA’s initiative to address the risks posed by cosmic rays on the International Space Station. Through a crowdsourcing campaign, NASA invited global participation to tackle this critical challenge.[1] The response was impressive, with over a thousand proposals submitted. The evaluation process yielded four exceptional solutions, and their creators were awarded monetary prizes.

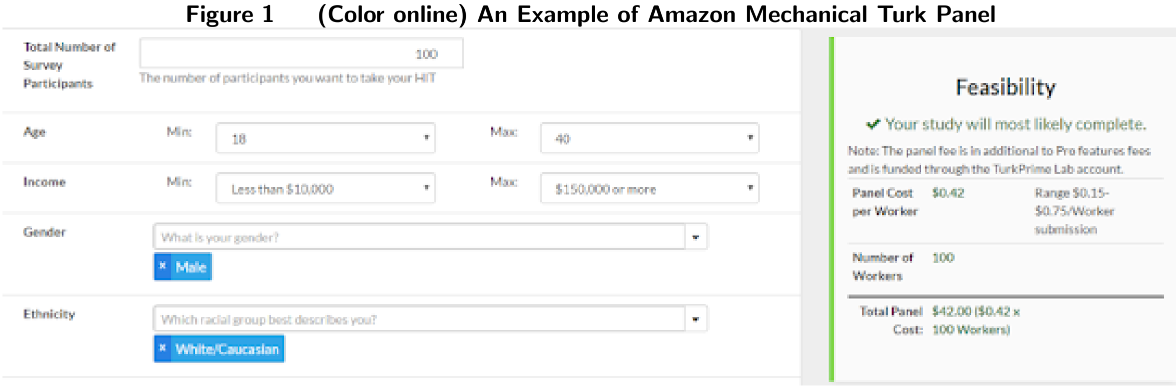
While initiatives like NASA’s demonstrate the potential of crowdsourcing, concerns regarding the quality of submissions frequently arise, particularly outside of contest-driven settings. Many crowdsourcing platforms, like Amazon Mechanical Turk, prioritize participation over selection by

[1] The NASA Innovation Pavilion launched the Reducing Exposure to Galactic Cosmic Rays Challenge on April 30, 2015, which concluded on June 29, 2015. Additional details are available at https://www.nasa.gov/general/reducing-exposure-to-galactic-cosmic-rays-challenge.

accepting and compensating a large volume of submissions for tasks such as image tagging or survey. This approach can cause “free-riding,” where participants invest minimal effort, knowing that even low-quality work might be accepted (Gadiraju et al. 2015, Kennedy et al. 2020). In more severe cases, some submissions may even originate from bots (Stokel-Walker 2018). The resulting influx of unproductive submissions can impede progress (Acar 2019). Additionally, the expertise, commitment, and motivation of participants vary considerably, leading to further inconsistencies in submission quality (Malone et al. 2010). Therefore, while crowdsourcing offers an undeniable advantage for harnessing global expertise and ideas, ensuring consistent quality remains a significant challenge that necessitates strategic oversight and innovative management solutions.

Researchers have explored various methods to enhance the quality of outcomes in crowdsourcing (see Daniel et al. 2018 for a review of quality control in crowdsourcing). These methods include organizing contests where rewards are based on crowdworker performance (e.g., Terwiesch and Xu 2008, Boudreau et al. 2011, 2016, Ales et al. 2017, Körpeoğlu and Cho 2018, Wang et al. 2019, Mo et al. 2021), and providing guidance through exemplars or feedback before or during tasks (e.g., Chan et al. 2021, Manshadi and Rodilitz 2022, Ta et al. 2021, Jian et al. 2019, Althuizen and Chen 2022, Koh and Cheung 2022, Sanyal and Ye 2024).

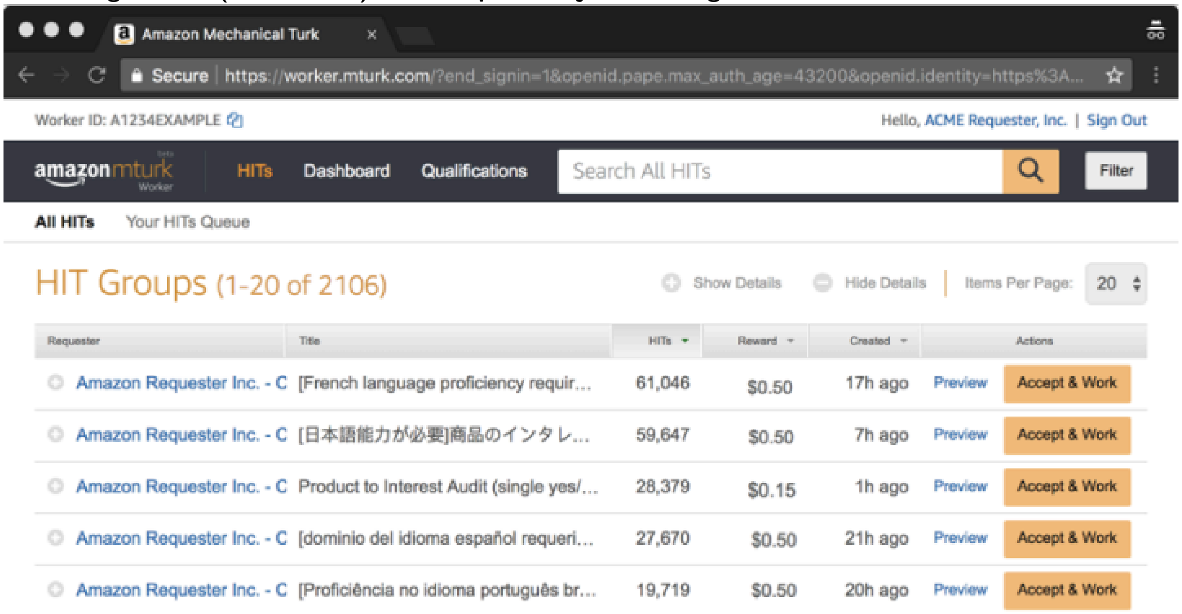
Figure 1 (Color online) An Example of Amazon Mechanical Turk Panel



Note. The requester can select demographic criteria. In this example, the cost for white males aged 40 and under is $0.42 per completion. Source: CloudResearch (`https://www.cloudresearch.com/resources/blog/mturk-panels-on-your-own-requester-account/`). Accessed on April 4, 2025.

A common yet underexplored practice in crowdsourcing is the use of rejection design. This design allows requesters to decline low-quality submissions, which encourages crowdworkers to deliver better work. Unlike contest-based models that reward only the top performers, the rejection design often accepts a broader range of submissions. To better illustrate the process, Figure 1 shows the process of hiring crowdworkers on Amazon Mechanical Turk, where the requester specifies the demographic criteria and the platform charges a service fee for hiring participants that meet these requirements. After collecting the submissions, the requester has the option to preview each

Figure 2 (Color online) An Example of Rejection Design from Amazon Mechanical Turk



Note. The requester can preview a worker's submission and has the option to decide whether to accept it. Source: Amazon Mechanical Turk Developer Guide (https://docs.aws.amazon.com/pdfs/AWSMechTurk/latest/AWSMechanicalTurkRequester/amt-dg.pdf). Accessed on April 4, 2025.

Table 1 Pricing Structures Across Major Crowdsourcing Platforms

Platform Name	Platform Type	Pricing Structure
Prolific	Survey	42.8% corporate, 33.3% academia/non-profit fees
Qualtrics	Survey	Varies by project needs
SurveyMonkey	Survey	Varies by project needs
Amazon Mechanical Turk	Microtasking	20% fee
Clickworker	Microtasking	40% fee
Appen	Microtasking	20% fee
Fiverr	Freelance	5.5% fee, plus $3 for orders under $100
Upwork	Freelance	3-10% fee, varies by plan
Freelancer	Freelance	3% fee or $3 minimum fee

Note: Major crowdsourcing platforms collect a commission from the total payment made by requesters to crowdworkers. This commission can either be a fixed percentage, such as a "20% service fee" on rewards or bonuses, or it may vary based on the specifics of the task.

submission and make decisions regarding acceptance, as shown in Figure 2. Similar to Amazon Mechanical Turk, other survey platforms like Prolific and Credamo, as well as freelancer platforms such as Upwork and Freelancer.com, also permit requesters to reject submissions that do not meet specified criteria.

The widespread adoption of the rejection design on major platforms underscores its importance, but its implementations vary significantly. In Table 1, we review the pricing strategies of major crowdsourcing platforms.[2] Most platforms take a fixed portion of the rewards or bonuses designated

[2] Pricing information for these platforms can be found on their respective websites: Prolific, https://researcher-help.prolific.com/en/article/9cd998; Qualtrics, https://www.qualtrics.com/support/

for crowdworkers. Only Qualtrics and Survey Monkey implement a granular pricing strategy that varies based on task characteristics. Notably, none of these platforms explicitly incorporate costs associated with rejection into their pricing models.

Despite its operational significance, the rejection design remains a source of contention. Critics argue that it can provoke behaviors that undermine platform reputation. Research indicates that rejection may prompt crowdworkers to avoid new requesters and choose only lower-risk tasks (McInnis et al. 2016). Some crowdworkers have developed protective measures, such as browser plugins that filter tasks and online forums where they propose improvements to platforms (Semuels 2018). In a worse case, those who experience rejection might voice their grievances on these forums.[3]

These dynamics raise several important questions that this paper seeks to address: (1) How does the implementation of the rejection design influence the quality of submissions? (2) What factors guide requesters and platforms in deciding to adopt the rejection design, and how do they determine the most effective strategies for its use? (3) How does the rejection design influence every party's welfare?

To address these questions, we introduce an analytical model that explores the dynamics among a crowdsourcing platform, a requester, and a large pool of crowdworkers. This model explores how the platform, acting as an intermediary that absorbs risks associated with recruitment and reputation, strategically establishes a menu of service fees charged to the requester for each submission. The model notably distinguishes between two types of service fees: one incurred for the submission accepted and another upon rejection. Influenced by the platform's pricing strategy, the requester decides not only the compensation for crowdworkers, but also an acceptance rate. We demonstrate that the rejection design prompts crowdworkers to engage in a discriminatory all-pay auction with single-unit demand. In this auction, crowdworkers "bid" their effort for the limited chances to be accepted and compensated, with their probability of being accepted depending on the quality ranking of their submissions.[4] We employ this auction framework for its versatility, which supports both contest scenarios—where only a few crowdworkers are declared winners (and the rest are "rejected")—and more inclusive tasks, such as online surveys, where a substantial portion of submissions are accepted.

`survey-platform/distributions-module/online-panels/`; SurveyMonkey, `https://help.surveymonkey.com/en/surveymonkey/send/surveymonkey-audience/`; Amazon Mechanical Turk, `https://www.mturk.com/pricing`; Clickworker, `https://www.clickworker.com/pricing/`; Appen, `https://success.appen.com/hc/en-us/articles/202703165-Job-Costs-FAQ`; Fiverr, `https://www.fiverr.com/legal-portal/legal-terms/payment-terms-of-service`; Upwork, `https://www.upwork.com/pricing/client`; Freelancer, `https://www.freelancer.com/feesandcharges`.

[3] Figure A.1 in Online Appendix A presents an example from Reddit, a social platform where users share and discuss content within niche communities, illustrating a complaint from individuals who were rejected.

[4] For more detailed definitions of discriminatory auction, all-pay auction, and single-unit demand, please refer to Krishna (2009).

Our analysis generates several intriguing findings. For crowdworkers, we focus on the optimal responses of submission quality. The results indicate that the rejection design is efficient, meaning that crowdworkers capable of providing higher-quality submissions at lower costs consistently submit superior work. We further explore the factors that influence the crowdworkers' decisions. We discover that varying the acceptance rate impacts crowdworkers differently. Specifically, it sets the ceiling for submission quality across all crowdworkers. Furthermore, as the number of crowdworkers increases, high-ability individuals are encouraged to reach this peak, while those with lower abilities tend to produce submissions of lower quality. This observation aligns with the empirical findings reported by Boudreau et al. (2016), which indicate that competition, driven by rankings, motivates the most skilled participants to improve their performance, while it tends to demotivate those with lower skills.

We next assess the optimality of the rejection design from the requester's perspective by comparing it with a theoretical supremum in full information scenario where crowdworkers have complete visibility of each other's capabilities. Although the full information scenario is typically impractical for real-world applications, it provides a valuable benchmark for assessing the rejection design. Our findings reveal that, initially, the rejection design yields a lower overall quality than this benchmark due to uncertainties related to the unknown capabilities of others. However, our analysis indicates that as the number of crowdworkers increases, this informational disadvantage diminishes, and the outcome of the rejection design converges to the benchmark. This finding suggests the approximate optimality of the rejection design. Furthermore, our findings highlight an important aspect: the rejection design functions as an implicit communication channel. The requester can leverage it to set expectations for submission quality, while crowdworkers can use this guidance to inform their decisions about submission quality.

By analyzing the dynamics between the platform and the requester, we observe that the adoption of the rejection design is largely influenced by potential costs the platform faces, such as the marginal recruitment cost for each crowdworker and the reputation loss due to rejection. Adoption is more likely when there is low reputation loss and low recruitment cost. Conversely, if the reputation loss is too high, the platform tends to charge a higher service fee to deter the requester from using the rejection design. Additionally, when the recruitment cost is also high, the platform struggles to find a strategy that ensures nonnegative utility for both itself and the requester, potentially leading to market exit. We also find that the crowdworkers' ability range significantly affect the adoption of the rejection design. A higher ability range may motivate the requester to pay more, thus offsetting the platform's costs. Moreover, if the requester can derive a higher quality-invariant utility from each accepted submission, the platform can capitalize on this surplus to cover its recruitment cost, which further increases the likelihood of adopting the rejection design. These insights are crucial for refining the platform's pricing strategy.

In the final part of our analysis, we examine changes in welfare resulting from the adoption of the rejection design. We discover that the platform benefits from additional revenue sources from rejected submissions, contrasting with scenarios involving no rejection design. Moreover, compared to the commonly adopted fixed minimum acceptance rate, our proposed rejection design allows the platform to use service fees to curb the requester's misuse of rejection and avoid unnecessary costs. Surprisingly, we also discover that the rejection design addresses potential inefficiencies arising from separate decision-making by the platform and the requester. In the first-best scenario where the platform and the requester are integrated, they reach identical conclusions regarding the acceptance rate and crowdworker compensation compared to a situation where they operate as separate entities. Therefore, the rejection design is unequivocally advantageous for the platform. Interestingly, we find that the overall crowdworker welfare also increases with the adoption of the rejection design. This counterintuitive outcome occurs because the rejection design, by eliminating free-riding behavior, encourages the requester to offer higher compensation for better quality submissions. These findings further validate the effectiveness of the rejection design.

The contribution of our study is threefold. First, it enhances the literature on crowdsourcing platforms by examining the rejection design, a widely practiced but scarcely explored aspect within academic research. We analyze the effectiveness and efficiency of the rejection design, developing optimal strategies for both requesters and platforms. Our findings deepen the understanding of quality control in crowdsourcing and introduce a novel menu pricing strategy for crowdsourcing platform. This new strategy not only aligns with real-world rejection policies but also offers insights into a more adaptable rejection design. Second, this study contributes to the growing literature on pricing strategies in the context of platform-based markets. Prior research has primarily focused on media platforms (e.g., Lin 2020, Amaldoss et al. 2021, 2024), retail platforms (e.g., Zhang and Chung 2020, Qiu and Rao 2024, Wang and Qiu 2024), and service platforms such as ride-sharing (e.g., Guda and Subramanian 2019, Besbes et al. 2021, Garg and Nazerzadeh 2022). However, pricing strategies within crowdsourcing platforms remain largely underexplored. To the best of our knowledge, this study is the first to examine how pricing can be strategically designed for crowdsourcing tasks—particularly through mechanisms such as rejection fees—to improve platform efficiency and align incentives among stakeholders. Third, our research extends to the literature on the application of auctions. In this paper, we demonstrate that crowdworker behavior in crowdsourcing tasks employing a rejection design can be effectively modeled through a discriminatory all-pay auction with single-unit demand. We explore the efficiency of this auction type and identify critical factors that influence auction outcomes. This analysis enhances the understanding of how auctions can be strategically used in studying crowdsourcing platform design, which broadens the scope of auction theory in practical settings.

Our study presents significant implications. First, our analysis demonstrates the efficiency of the rejection design from the crowdworkers' perspective and its optimality from the requester's viewpoint. We show that the rejection design motivates high-ability crowdworkers to provide higher-quality submissions and it also closely mirrors the theoretical supremum in full information scenarios when the crowdworker pool is large. These findings imply that the requester can effectively use the rejection design as a powerful tool to improve crowdsourcing outcomes. Second, our results indicate that crowdsourcing platforms could enhance their revenue models by charging requesters a service fee for rejected submissions. Typically, major crowdsourcing platforms establish a fixed minimum acceptance rate and offer refunds to requesters for rejected submissions. We argue that these practices are suboptimal. Based on our analysis of the interaction between a platform and a requester, we recommend a more sophisticated pricing strategy through our proposed rejection design. Third, it is noteworthy that our findings also suggest an increase in the welfare of crowdworkers under the rejection design, creating a win-win-win scenario for the platform, the requester, and crowdworkers. This result provides crowdsourcing platforms with additional evidence to support the adoption of the rejection design.

2. Literature

Research on crowdsourcing primarily focuses on two main areas. The first encompasses downstream processes, including post-crowdsourcing idea screening (Kornish and Jones 2021, Bell et al. 2024), subsequent impacts such as how crowdsourcing-based product features or labels affect sales (Gu et al. 2022, Nishikawa et al. 2017), the influences on shareholder value (Cao et al. 2024), and the identification of potential biases in crowdsourced outcomes (Kwan et al. 2024). Our study, however, contributes to the second stream, which addresses mechanism design within the crowdsourcing tasks themselves. This research area aims to enhance the direct outcomes of crowdsourcing activities by examining optimal task design. In particular, our paper focuses on quality control within crowdsourcing platforms, bridging two interconnected literatures: contest design and information provision. We review relevant literature to situate our research within this broader scholarly context, highlighting our study's unique contributions and clarifying how it builds upon and diverges from established methodologies.

Quality Control through Contest Design. Contests have a well-established role in incentivizing high-quality outcomes by fostering structured competition that promotes innovation and enhanced performance. Existing research extensively explores various contest design features, including outcome disclosure (Hossain et al. 2019), player matching (Ridlon and Shin 2013), joint versus separate goal pursuit (Hu and Wang 2021), participant numbers (Tian et al. 2022), contest duration (Chen et al. 2021), task complexity (Mo et al. 2021), submission visibility (Bockstedt et al. 2022, Hofstetter et al. 2021), competitive intensity (Körpeoğlu and Cho 2018, Wang et al. 2019), and the structure of rewards and punishments (Kalra and Shi 2001, Thomas and Wang 2013, Kamijo 2016, Liu and Lu 2023). Building on this extensive literature, our study specifically investigates the unique dynamics introduced by the rejection design in crowdsourcing tasks. Analogous to mechanisms discussed in prior studies, the rejection design intensifies competition by implementing lower acceptance rates, incentivizing crowdworkers to provide higher-quality submissions to avoid rejection. Additionally, our research connects closely with studies on compensation and reward design in contests, as requesters must strategically set compensation levels that align with their desired acceptance rate and balance cost and output quality.

We model the rejection design as a competitive contest where crowdworkers compete for limited acceptance opportunities. We utilize the theoretical framework of all-pay auction to capture crowdworkers' strategic choices. In this scenario, crowdworkers possess private information regarding their capabilities and employ Bayesian Nash equilibrium reasoning to determine optimal submission quality levels. Providing certain level of submission quality in our context is similar to formulating a bid in an auction. Unlike traditional auctions, where only winning bidders incur costs, in all-pay auctions, all participants bear costs irrespective of success (Krishna 2009). This all-pay auction framework is well-established in the literature for its efficacy in examining highly competitive environments. Pioneering work by Moldovanu and Sela (2001) use this framework to model rank-order contests with incomplete information. Subsequent studies, such as those by Kamijo (2016) and Liu and Lu (2023), investigate how specific incentives, including top rewards and bottom punishments, can significantly enhance the performance within teams. Building on these foundations, our analysis explores strategic trade-offs faced by crowdworkers through a discriminatory all-pay auction with single-unit demand, providing deeper insights into behavioral dynamics in crowdsourcing contests.

Quality Control through Information Providing. Another important dimension of ensuring quality in crowdsourcing platforms is providing clear and targeted information to participants. One prevalent strategy involves providing explicit guidance or exemplar information before tasks commence, which clarifies requesters' expectations and helps crowdworkers align their submissions accordingly. In previous studies, Ta et al. (2021) demonstrate that task framing significantly influences participants' comprehension and performance, while Cao et al. (2024) study the signal effects of contest design factors and firm marketing resources on crowdsourcing outcomes. Further, Koh (2019), Althuizen and Chen (2022), and Koh and Cheung (2022) highlight both beneficial and restrictive effects of presenting exemplars. Notably, Althuizen and Chen (2022) and Koh and

Cheung (2022) point out that exemplar guidance may inadvertently constrain creativity. This disadvantage restricts the use of exemplar in crowdsourcing tasks.

Providing real-time feedback during tasks represents another effective information approach to quality control. Chan et al. (2021) and Sanyal and Ye (2024) indicate that various feedback types—including positive, negative, peer-generated, or firm-directed—have distinct impacts on crowdworker performance. Additionally, studies by Wooten and Ulrich (2017) and Jiang et al. (2022) compare different feedback mechanisms (e.g., random versus direct feedback) and their efficacy. Community development is also identified as a valuable mechanism for enhancing performance through knowledge sharing and interaction. Prior studies by Bayus (2013), Huang et al. (2014), Majchrzak and Malhotra (2016), Camacho et al. (2019), Hwang et al. (2019), and Jin et al. (2021) underscore the benefits of fostering collaborative, interactive communities among crowdworkers.

These diverse informational strategies emphasize the crucial role that structured communication plays in improving crowdsourcing quality. Although our rejection design does not involve explicit guidance or real-time feedback, it inherently communicates requester standards through the acceptance rate. Our analysis suggests that this implicit message effectively informs crowdworkers about expectations, which further guides their decisions about effort and submission quality. Thus, our proposed rejection design bypasses complexities related to exemplar effects and leverages competitive dynamics innovatively, presenting a novel mechanism to direct participant efforts without traditional, explicit feedback methods.

3. Model

A typical crowdsourcing task begins with a requester publicly posting a clearly defined assignment on an online platform. The platform then invites a large pool of crowdworkers to participate and charges the requester a service fee. Crowdworkers independently complete the task in exchange for compensation or other incentives. The requester subsequently collects, aggregates, and utilizes these individual contributions to fulfill a broader objective.[5]

Built on this basic process, we develop a general framework to effectively capture various dynamics among a crowdsourcing platform, a requester, and multiple crowdworkers in a real world scenario. An important feature in our model is that the requester can determine an *acceptance rate* before publishing a task.[6] This rate specifies the maximum number of submissions the requester can reject. As a result, the threat of rejection motivates crowdworkers to deliver higher-quality contributions.

[5] This procedure reflects standard industry practice. For further details on its benefits, protocols, and case studies, see Qualtrics (https://www.qualtrics.com/experience-management/research/research-panels-samples/) and SurveyMonkey (https://www.surveymonkey.com/market-research/resources/online-market-research-panels/).

[6] In the extension, we examine scenarios in which different parties are responsible for determining the acceptance rate.

If rejection carries no costs, the requester might abuse it. Therefore, we also allow the platform to mitigate this risk by presenting a menu of service fees regarding both the accepted and rejected submissions. The service fee of rejection in our model serves dual purposes. First, the platform generates additional revenue in scenarios where the requester strategically employs the rejection design to enhance submission quality. Second, it compensates for the costs caused by recruitment challenges and reputation damage arising from rejections.

The setting of our model is compatible with multiple different scenarios in practice. For example, if the acceptance rate is set to one, the model reduces to the most basic case where rejection is not allowed. If the acceptance rate is less than one and the service fee for rejection is zero, the model aligns to many platforms' practice (e.g., Amazon Mechanical Turk).

In the following sections, we provide formal definitions and detailed explanations regarding the utility functions of all parties involved.

3.1. Crowdworker

A group of crowdworkers are recruited through the platform to complete a crowdsourcing task. Each crowdworker, labeled as i, strategically decides on the submission quality q_i and earns a compensation of w if the submission is accepted. We assume that crowdworkers are risk-neutral. The cost for crowdworker i to provide a submission of quality q_i is $\frac{q_i}{s_i}$, where s_i represents crowdworker i's effectiveness in converting effort to quality.[7] The utility of crowdworker i, denoted as U_i^C, is $w - \frac{q_i}{s_i}$ if his submission is accepted and $-\frac{q_i}{s_i}$ if rejected.

We assume s_i is heterogeneous and is independently drawn from a uniform distribution on $[0, \bar{s}]$, where $\bar{s}$ is a predetermined characteristic.[8] A smaller s_i makes it difficult to enhance submission quality regardless of the effort exerted. Conversely, a larger s_i allows a crowdworker to achieve higher quality at a lower cost. We further assume that only crowdworkers themselves can observe their own s_i, but the distribution of s_i is a common knowledge. For simplicity, we refer to $\bar{s}$ as the ability range hereafter.

The platform hires n crowdworkers. Let $q_{-i,j}$ denote the j-th highest submission quality among the $n-1$ crowdworkers excluding individual i. Suppose that the requester accepts only the top m submissions (corresponding with an acceptance rate of $\pi = \frac{m}{n}$) with relatively higher quality and

[7] This setting is consistent with Liu et al. (2014), where the authors also consider a conversion of effort into quality. Similar model specification can also be found in the tournament contract model (Bolton and Dewatripont 2004).

[8] Lemmas B.1 and B.2 in Online Appendix B suggest that our analysis on the efficiency of the rejection design remains robust across various distributions of crowdworker ability. Nevertheless, this simplification is essential for deriving closed-form expressions for the equilibrium between the platform and the requester.

rejects the rest. Crowdworker i's submission will be accepted if and only if $q_i > q_{-i,m}$. Thus, the utility function of crowdworker i is as follows:[9]

$$U_i^C = \begin{cases} w - \frac{q_i}{s_i} & \text{if } q_i > q_{-i,m} \\ -\frac{q_i}{s_i} & \text{if } q_i < q_{-i,m} \end{cases}.$$

This equation highlights the trade-off each crowdworker faces between exerting more effort to ensure acceptance and minimizing effort to reduce costs.

3.2. Requester

The requester maximizes her utility by determining the acceptance rate π and the compensation for crowdworkers w. The utility derived from accepted submissions is twofold. First, the requester experiences diminishing marginal utility from the quality of each submission, modeled as q_i^α, where $0 < \alpha < 1$ ensures a concave utility function.[10] We set $\alpha = \frac{1}{2}$ for the remainder of the analysis for the purpose of tractability. This model setting aligns with classical economic theories of diminishing marginal returns (Sundararajan 2004, Abhishek et al. 2016, Chellappa and Mehra 2018, Gu and Zhao 2024). To illustrate this practically, note that initial improvements in submission quality—such as transitioning from irrelevant or inaccurate responses to moderately accurate ones—typically result in significant value enhancement for the requester. However, once submissions have already reached a high-quality threshold, further incremental improvements contribute relatively less additional value. For instance, in data-labeling tasks, improving labels from inaccurate to generally accurate significantly enhances downstream analysis. However, further improvements—from already accurate to nearly perfect labels—may not meaningfully increase overall efficiency. In fact, overly detailed submissions might require additional effort to process without correspondingly improving downstream performance. Therefore, in many real-world crowdsourcing scenarios, requesters naturally experience diminishing returns as submission quality approaches higher levels. Second, the requester also gains a quality-invariant utility from each accepted submission. For example, when the downstream analysis involves statistical inference, each accepted submission contributes to the robustness of the analysis. In such cases, part of the utility is driven by the quantity of submissions rather than their individual quality. We denote this component of utility as a. In the extreme case where the requester utility comes solely from submission quality, we have $a = 0$.

The cost associated with each accepted submission comprises the crowdworker's compensation w and the platform service fee c_1. Conversely, while rejected submissions yield no utility for the

[9] We omit $q_i = q_{-i,m}$ as the event has zero probability measure.

[10] This method of modeling diminishing marginal utility aligns with Currarini et al. (2009) and Leung (2020).

requester, she still incurs a service fee c_2 for each. The requester's utility from crowdworker i's submission is defined as

$$U_i^R = \begin{cases} \sqrt{q_i} + a - w - c_1 & \text{if } q_i > q_{-i,m} \\ -c_2 & \text{if } q_i < q_{-i,m} \end{cases}.$$

The total utility of the requester is represented as the sum of the utilities derived from each crowdworker's submission, expressed as $U^R = \sum_{i=1}^{n} U_i^R$.

3.3. Platform

The platform optimizes its utility by strategically deciding the menu of service fees, charging c_1 for each accepted submission and c_2 for each rejection. The platform incurs costs related to recruitment efforts and potential reputation damage. The recruitment cost, denoted as h, is incurred for every crowdworker regardless of whether their submission is accepted or not. In contrast, the reputation loss, denoted as r, only occurs for each rejected submission because individuals who are rejected may use social media to express their dissatisfaction, potentially harming the platform's reputation. This configuration underscores an important role of crowdsourcing platforms as efficient intermediaries that mitigate risks associated with the recruitment process and dissatisfaction from crowdworkers. The utility derived by the platform from crowdworker i's submission is defined as follows:

$$U_i^P = \begin{cases} c_1 - h & \text{if } q_i > q_{-i,m} \\ c_2 - h - r & \text{if } q_i < q_{-i,m} \end{cases}.$$

The total utility of the platform is then calculated as the sum of the utilities derived from each crowdworker, expressed as $U^P = \sum_{i=1}^{n} U_i^P$.

3.4. Timeline of the Game and Notations

Figure 3 Timeline of the Game

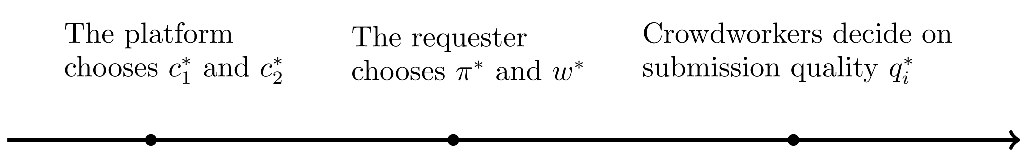


Figure 3 outlines the timeline of the game. The sample size requirement m and ability range $\bar{s}$ are assumed predetermined. The game begins with the platform's decision on the menu of service fees for both acceptance (c_1^*) and rejection (c_2^*). Following this, the requester determines the acceptance rate π^* and the compensation w^* for crowdworkers. Finally, a group of crowdworkers, having been recruited by the platform, decides on the quality of their submissions q_i^*.

Table 2 presents a summary of the key notations employed in our model. In the following section, we provide a formal analysis of the game.

Table 2 Key Model Notation

Notation	Meaning
Crowdworker type and decision	
s_i	Crowdworker ability
q_i	Submission quality
Requester decision	
π	Acceptance rate
w	Compensation for crowdworkers
Platform decision	
c_1	Service fee for accepted submissions
c_2	Service fee for rejected submissions
Pre-determined parameter	
a	Constant part of requester's marginal utility from accepted submissions
$\bar{s}$	Ability range
m	Required number of participants for the crowdsourcing task
r	Reputation damage on the platform due to a rejection
h	Marginal recruitment cost

4. Analysis and Results

In this section, we present the equilibrium results of our model. Using backward induction, we first derive the strategy for the crowdworkers, followed by the requester, and finally the platform. We provide proof details in Online Appendix C.

4.1. Crowdworker Decision

We focus on symmetric equilibria, where all crowdworkers adopt the same decision rule initially, with their subsequent behaviors varying solely due to their individually distinct abilities s_i. We assume that s_i is private information. The crowdworkers also know that the requester selects the top m submissions for acceptance after assessing the submission quality from $n = \frac{m}{\pi}$ crowdworkers. We solve for crowdworker decisions using the framework of discriminatory all-pay auction with single-unit demand. In this model, m items are available, each representing a chance for acceptance, with each crowdworker eligible to secure only one opportunity. Crowdworkers incur costs through bidding for the opportunity regardless of acceptance, where their bids represent the cost for achieving a certain submission quality. Since crowdworkers can observe only their own types, each of them solves $\max_{q_i} \mathbb{E}[U_i^C]$. Following Krishna (2009), we derive the crowdworkers' optimal responses and present the following lemma.

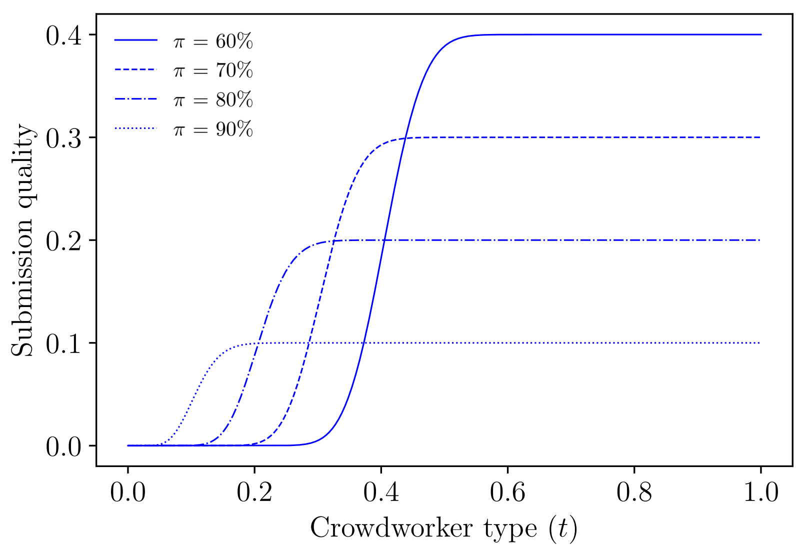
Lemma 1. *(Optimal Crowdworker Submission Quality) The optimal submission quality for crowdworker i is given by:*

$$q_i^* = w\bar{s}(1-\pi)I_{s_i/\bar{s}}((1-\pi)n+1, \pi n). \tag{1}$$

In Equation 1, $I_x(z_1, z_2) = \text{Beta}_x(z_1, z_2)/\text{Beta}(z_1, z_2)$ represents the regularized incomplete beta function, where $\text{Beta}(z_1, z_2) = \int_0^1 x^{z_1-1}(1-x)^{z_2-1}dx$ defines the beta function, and $\text{Beta}_x(z_1, z_2) = \int_0^x x^{z_1-1}(1-x)^{z_2-1}dx$ defines the incomplete beta function. The lemma describes the optimal response in terms of submission quality within the Bayesian Nash equilibrium framework. When $\pi = 1$, crowdworkers are assured of acceptance, thus the optimal response is to provide zero quality as it minimizes the cost. Conversely, when $0 < \pi < 1$, the submission quality increases with both the compensation w and the ability range $\bar{s}$. This aligns with the intuitive understanding that higher rewards and better abilities synergistically ensure that crowdworkers are both motivated and capable of producing quality work. This lemma also reveals that crowdworkers consider the acceptance rate and expected ability ranking when determining the quality of their submissions. The properties of crowdworker optimal response are further elucidated in subsequent propositions. The next proposition demonstrates that the rejection design, characterized by an acceptance rate potentially less than one, promotes efficiency.[11]

PROPOSITION 1. *(Efficiency of Rejection Design) If the acceptance is not assured, crowdworkers with higher abilities consistently provide submissions with higher quality, that is,* $\frac{\partial q_i}{\partial s_i} > 0$.

Figure 4 Optimal Submission Quality Across Different Acceptance Rate



Note. $w = 1$, $n = 100$, $\bar{s} = 1$.

This proposition is particularly intriguing as it shows that the acceptance rate itself effectively communicates the requester's expected quality standards. We observe that crowdworkers who are capable of providing superior submissions at a lower cost are more likely to do so and hence their

[11] In an auction, efficiency is defined as the object being awarded to the participant who values it the most (Krishna 2009). In our context, it refers to the acceptance being allocated to higher-ability crowdworkers.

submissions are more likely to be accepted. This suggests the efficiency of the rejection design. An explanation for this behavior is that crowdworkers initially estimate their competitive standing based on their own types s_i within the recruited group. A higher perceived ranking indicates a higher competence and hence incentivizes the crowdworker to submit higher-quality work. This dynamic is further illustrated in Figure 4, which shows that submission quality monotonically increases with ability across various acceptance rates.

Proposition 1 indicates that adopting the rejection design benefits both the crowdworkers and the requester. From the crowdworkers' perspective, the rejection design ensures fair competition by aligning their abilities with the task requirements. Those with higher abilities are consistently encouraged and more likely to be accepted. From the requester's viewpoint, this design helps identify and support the most suitable crowdworkers, motivating them to provide higher-quality submissions. As a result, free-riding, a common concern on crowdsourcing platforms, is no longer a dominant strategy under the rejection design. This dual perspective significantly boosts the overall effectiveness and efficiency of crowdsourcing. In addition to these benefits, the rejection design also enhances the welfare of both the platform and the crowdworkers, which will be discussed later in Propositions 5 and 6.

In the following propositions, we explore the characteristics of crowdworkers' optimal strategies. We first examine how the requester's strategic decision regarding the acceptance rate influences these optimal strategies.

PROPOSITION 2. *(Submission Quality and Acceptance Rate) There exists a least upper bound, $w\bar{s}(1-\pi)$, for submission quality. A lower acceptance rate results in a higher least upper bound for submission quality.*

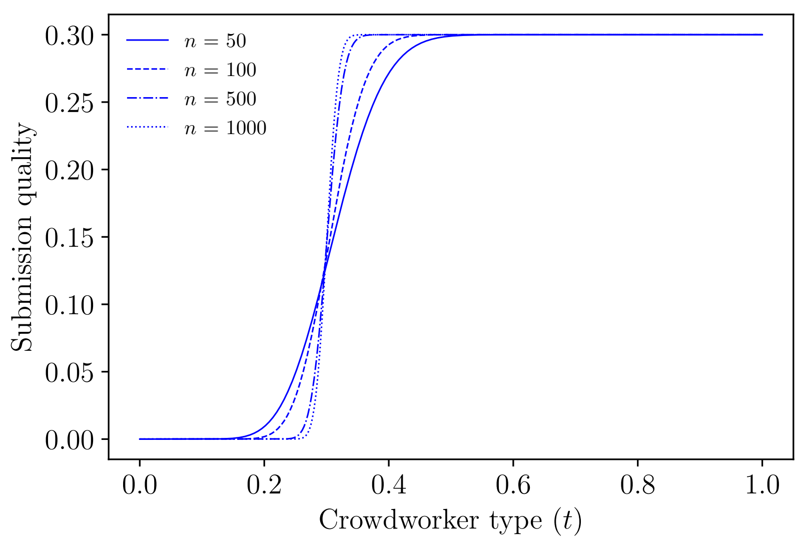
This proposition focuses on the optimal responses from higher-ability crowdworkers—those with a higher s_i, whose optimal responses of submission quality tend to be closer to $w\bar{s}(1-\pi)$. When the requester chooses a higher acceptance rate, these crowdworkers might provide lower-quality submissions since they know that they can secure a payoff with minimal concern about being rejected for lower-quality submissions. In an extreme scenario, where the requester accepts every submission and sets $\pi = 1$, q_i^* becomes zero, which creates a completely free-riding situation due to the absence of rejection as a deterrent. Conversely, introducing a lower acceptance rate through the rejection design could intensify competition, forcing higher-ability crowdworkers to deliver higher-quality submissions to ensure acceptance. While this leads to more rejections, the accepted submissions are of high quality. It is crucial to note, however, that even the most capable crowdworkers will not improve their quality beyond $w\bar{s}(1-\pi)$, as there is no incentive for others to exceed this quality level due to ability limits. Hence, for those high-ability crowdworkers, making additional effort becomes ineffective in enhancing the likelihood of acceptance. This finding underscores the importance of strategically selecting an acceptance rate.

Proposition 2 reveals two significant implications. First, if the requester aims to maintain a certain level of quality among accepted submissions, reducing the acceptance rate could be an effective strategy. This approach would increase the likelihood of being rejected, thereby motivating the remaining participants to provide higher-quality submissions. Second, using the acceptance rate as an incentive has its limitations, as it does not indefinitely increase the submission quality from high-ability crowdworkers. Additionally, it could demotivate a significant portion of crowdworkers. Therefore, indiscriminately lowering the acceptance rate may not always yield benefits. It is important to determine an optimal acceptance rate that strikes a balance between individual submission quality and the overall number of accepted submissions.

In addition to the acceptance rate, the expected ability ranking also significantly influences the optimal responses of crowdworkers. Its impact is further elucidated in the following proposition.

Proposition 3. *(Submission Quality and Ability Ranking) As the number of crowdworkers increases, a distinct pattern emerges based on their ability. For crowdworkers with low ability, specifically those for whom $s_i < \bar{s}(1-\pi)$, the submission quality converges to zero. Conversely, for those with high ability, where $s_i > \bar{s}(1-\pi)$, their submission quality converges to $w\bar{s}(1-\pi)$.*

Figure 5 **Optimal Submission Quality Across Different Sample Sizes**



Note. $w = 1$, $\pi = 0.7$, $\bar{s} = 1$.

Another critical factor influencing submission quality is the ability ranking among crowdworkers. Proposition 3 shows that crowdworkers assess the order statistic of their ability relative to all participants.[12] Figure 5 provides a visualization that helps elucidate this phenomenon. It shows that crowdworkers with higher abilities are more likely to produce high-quality submissions in crowdsourcing tasks that have more crowdworkers, whereas those with lower abilities may not. This effect arises because the number of crowdworkers in the task influences the uncertainty in individual assessments of ability rankings. More crowdworkers lead to reduced uncertainty in such assessments. Consequently, the probability of acceptance becomes more sharply defined around the ability threshold of $\bar{s}(1-\pi)$. In the extreme case where the number of crowdworkers approaches infinity, uncertainty is completely eliminated. As a result, individuals with $s_i > \bar{s}(1-\pi)$ consistently deliver a submission quality of $w\bar{s}(1-\pi)$, while others contribute zero submission quality. A significant implication of this finding is that the rejection design becomes more effective for larger crowdsourcing tasks. It motivates those with $s_i > \bar{s}(1-\pi)$ to submit higher-quality submissions due to a higher certainty of acceptance. Conversely, although those with $s_i < \bar{s}(1-\pi)$ might produce lower quality submissions in larger samples, their increased likelihood of being rejected helps maintain the overall quality of accepted work. This property highlights the scalability of the rejection design.

4.2. Requester Decision

As the crowdworker types are unobservable to the requester, her optimal response aims to maximize her expected utility, $EU^R = \mathbb{E}\left[\sum_{i=1}^{n} U_i^R\right]$, which is derived in the following lemma.

Lemma 2. *(Requester Expected Utility) The requester obtains the following expected utility*

$$EU^R = \underbrace{\frac{m}{\pi}\sqrt{w\bar{s}(1-\pi)}\int_0^1 \sqrt{I_x\left((1-\pi)\frac{m}{\pi}+1, m\right)I_x\left((1-\pi)\frac{m}{\pi}, m\right)}\,dx}_{\text{utility from submission quality}} + \underbrace{ma}_{\text{quality-invariant utility}} - \underbrace{mw}_{\text{compensation}} \underbrace{-mc_1 - \frac{m}{\pi}(1-\pi)c_2}_{\text{platform service fee}}. \tag{2}$$

In Equation 2, m represents the predefined number of submissions required for the task. Deriving closed-form solutions for the first term in Equation 2, which represents the total utility derived from submission quality, presents significant challenges. Therefore, our analysis begins by examining an ideal benchmark scenario where crowdworker types are public information. In this scenario, rejection is still available. The only difference is in the accessibility of information. In the subsequent lemma, we calculate the submission quality derived from the benchmark scenario, which we later use as a benchmark to assess the efficacy of the rejection design.

[12] Order statistics are frequently used to infer unobservable rankings. For example, Chung (2013) employ this approach to estimate applicant quality based on data from enrolled students.

LEMMA 3. *(Full Information Benchmark) Suppose that n crowdworkers are recruited and only $m < n$ submissions will be accepted. Assume that every crowdworker's ability is observable to all other players. Let s^m denote the m-th highest ability among all crowdworkers involved in the task. To ensure acceptance, the crowdworker i provides a submission quality of $q_i = ws^m$ if and only if $s_i \geq s^m$. Otherwise, he provides zero quality when $s_i < s^m$. Denote $\pi = \frac{m}{n}$. Then, the supremum of the requester's expected total utility from submission quality is $m\sqrt{w\bar{s}(1-\pi)}$.*

This lemma outlines a scenario where crowdworker ability is public information. In real-world settings, it is nearly impossible to encounter as crowdworkers typically do not observe each other's type. Most crowdsourcing tasks today are distributed through digital platforms where users remain anonymous to one another. Even when profiles are accessible, reliably discerning information about strangers is still a significant challenge. However, this scenario serves as a benchmark. By comparing the utility derived from submission quality between our model and this benchmark, we can better understand how information asymmetry causes efficiency losses. We further quantify the difference using the ratio $\tau = Q/\bar{Q}$, where $Q = \frac{m}{\pi}\sqrt{w\bar{s}(1-\pi)}\int_0^1 \sqrt{I_x((1-\pi)\frac{m}{\pi}+1, m)I_x((1-\pi)\frac{m}{\pi}, m)}dx$ is the first term in Equation 2, and $\bar{Q} = m\sqrt{w\bar{s}(1-\pi)}$ is the largest expected total utility that can be derived from a full information scenario. A larger τ indicates that the rejection design more closely approaches the efficiency of the benchmark. We derive the following proposition.

PROPOSITION 4. *(Approximate Optimality of Rejection Design) Although information asymmetry introduces efficiency loss in the rejection design (i.e., $\tau < 1$), this loss decreases as the number of crowdworkers increases (i.e., $\lim_{n\to\infty} \tau \to 1$).*

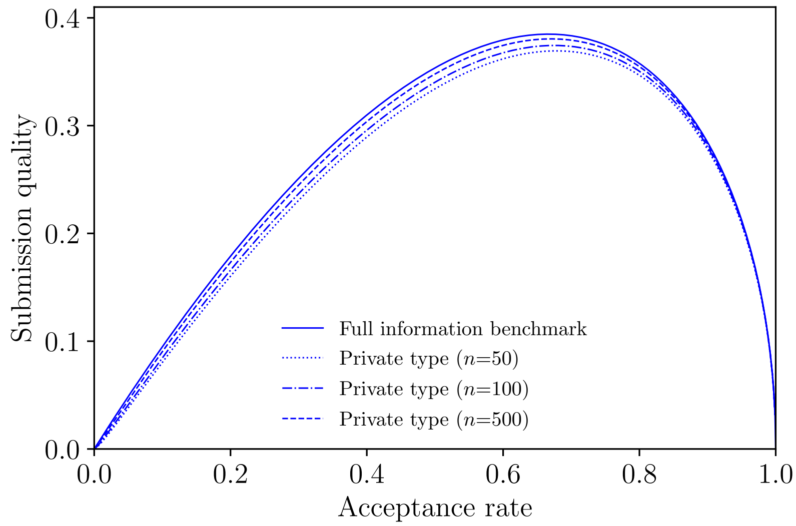
Table 3 **Efficiency Difference between Rejection Design and the Theoretical Supremum**

	$\pi = 20\%$	$\pi = 40\%$	$\pi = 60\%$	$\pi = 80\%$	$\pi = 99.9\%$
$n = 100$	0.078	0.048	0.032	0.021	0.006
$n = 200$	0.053	0.032	0.022	0.014	0.003
$n = 500$	0.033	0.020	0.013	0.008	0.001
$n = 1000$	0.023	0.014	0.009	0.006	0.001
$n = 2000$	0.016	0.010	0.006	0.004	0.000
$n = 5000$	0.010	0.006	0.004	0.003	0.000

Note. To measure the closeness of the quality-related utility derived from submissions between the two scenarios, we calculate the relative difference $(\bar{Q} - Q)/\bar{Q}$. A smaller value of this metric indicates greater closeness.

Proposition 4 reveals a particularly insightful and significant finding of our research. It shows that although the efficiency of the rejection design is initially lower than that of the full information benchmark, this gap diminishes substantially as the number of crowdworkers increases. This pattern highlights the scalability of the rejection design and its ability to approach benchmark efficiency in

Figure 6 Average Submission Quality Across Different Mechanisms



Note. $w = 1$, $\bar{s} = 1$.

expansive crowdsourcing settings. This finding resonates with the conclusions drawn in Green and Stokey (1983), where the authors demonstrated that the efficiency of a tournament improves with an increasing number of contestants. The intuition is the same as in Proposition 3, where a larger sample size reduces uncertainty and polarizes the likelihood of acceptance for submission quality on different sides of $w\bar{s}(1-\pi)$.

To emphasize the practical implications of our findings, we further show that the improved efficiency of the rejection design does not require an infinitely large number of crowdworkers to become evident. A series of numerical simulations demonstrate that even with moderate increases in crowdworker number, the efficiency of the rejection design rapidly approaches the benchmark. As depicted in Figure 6, the average submission quality obtained through the rejection design increasingly aligns with the benchmark across various acceptance rates. Furthermore, in Table 3, we report the relative differences between our model and the full information benchmark. We present the differences across five distinct acceptance rates. Notably, these differences diminish rapidly as the number of crowdworkers increases.

These simulations not only underscore the relevance of our findings for real-world applications but also suggest an effective simplification for analyzing the requester's utility derived from submission quality in Equation 2. Building on Proposition 4, we substitute the first term in Equation 2 with $m\sqrt{w\bar{s}(1-\pi)}$ for analytical purposes. This approximation shares the same intuition with a deterministic fluid model for large sample sizes, where a complex, often stochastic system is approximated using continuous, average-based behavior, ignoring the randomness or granularity of individual particles. This approach is commonly used in the revenue management literature (e.g., Talluri and Van Ryzin 2004, Gallego and Topaloglu 2019). Another similar approach can also be found in Olszewski and Siegel (2016), where the authors propose an approximation method in large scale contests. The method matches the position of a prize within the prize distribution by the position of the type within the type distribution to which the prize is allocated. By adopting this approximation, the requester's expected utility in Equation 2 simplifies to

$$EU^R = \underbrace{m\sqrt{w\bar{s}(1-\pi)} + ma}_{\text{utility from submissions}} - \underbrace{mw}_{\text{compensation}} - \underbrace{mc_1 - \frac{m}{\pi}(1-\pi)c_2}_{\text{platform service fee}}. \tag{3}$$

Based on this new requester utility function, we derive the requester's optimal strategy for choosing the acceptance rate π^* and crowdworker compensation w^* in the following lemma.

LEMMA 4. *(Requester's Optimal Strategy) If* $0 \le c_2 < \frac{\bar{s}}{4}$*, the requester chooses the acceptance rate at* $\pi = \frac{2\sqrt{c_2}}{\sqrt{\bar{s}}}$ *and the compensation for crowdworkers at* $w = \frac{\bar{s} - 2\sqrt{\bar{s}c_2}}{4}$*. If* $c_2 \ge \frac{\bar{s}}{4}$*, the requester sets* $\pi = 1$ *and* $w = 0$*.*

The selection of the acceptance rate is influenced by both the ability range, $\bar{s}$, and the platform's pricing strategy on rejection, c_2. If the task cannot acquire sufficiently capable crowdworkers, which is represented by a smaller ability range $\bar{s}$, or if the cost of rejection c_2 is too high—specifically, $c_2 \ge \frac{\bar{s}}{4}$—the requester will choose not to reject any submissions, resulting in a scenario where all submissions are accepted. This occurs because the cost of using rejection as an incentive mechanism exceeds the potential payoff gained from improved submission quality. Conversely, if the cost of rejection is low such that $0 \le c_2 < \frac{\bar{s}}{4}$, the requester is likely to use the rejection design. This lemma also underscores an important consideration: the cost of rejection should not be overlooked. If it were, the optimal strategy for a requester would involve recruiting a vast number of crowdworkers and setting a very low acceptance rate, which could potentially overburden the platform.

We note that when the requester sets $\pi = 1$, she also offers zero compensation. According to Lemma 1, crowdworkers receive zero utility in this case and are therefore indifferent between entering and exiting. When such indifference arises, we assume that crowdworkers choose to enter. This is because the requester can introduce a small, positive utility increment to the entry option, such that the crowdworkers' utility from entry becomes strictly greater than that from exit. This infinitesimal advantage effectively breaks the indifference and leads crowdworkers to prefer entry.[13]

[13] This approach is well-supported by industry practices. For instance, Schwann's Food Services does not employ a survey rewards program. Instead, they rely on a panel of brand-loyal members, achieving a 30-45% response rate on general customer surveys among these participants (Source: `https://www.qualtrics.com/experience-management/research/reward-your-research-panel/`). Additionally, a tutorial by SurveyMonkey indicates that, in some instances, offering no compensation can still lead to favorable outcomes (Source: `https://www.surveymonkey.com/mp/survey-prizes-pros-and-cons/`).

4.3. Platform Decision

The platform optimizes its expected utility by setting service fees for both accepted and rejected submissions, subject to the constraint that the requester's expected utility remains nonnegative, which is formulated as $\max_{c_1,c_2} \mathbb{E}[\sum_{i=1}^{n} U_i^P]$ s.t. $EU^R > 0$. We first derive the utility function of the platform through the following lemma.

Lemma 5. *(Platform Utility) The platform obtains the following expected utility*

$$EU^P = \underbrace{mc_1 + \frac{m}{\pi}(1-\pi)c_2}_{\textit{platform service fee}} - \underbrace{\frac{m}{\pi}(1-\pi)r}_{\textit{reputation loss}} - \underbrace{\frac{m}{\pi}h}_{\textit{hiring cost}} \quad . \tag{4}$$

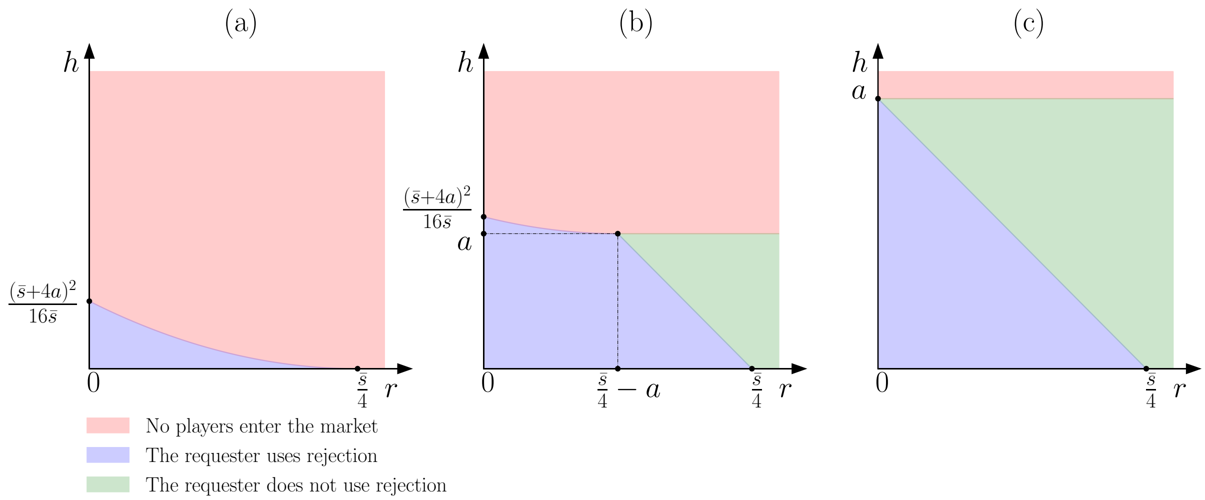
The platform's utility comprises three parts. The first part derives from charging service fees for both accepted and rejected submissions. The second part is the disutility resulting from reputation loss associated with each rejected crowdworker. The third part involves hiring costs incurred for each crowdworker, regardless of whether they are accepted or not. The determination of c_2 involves several trade-offs. As Lemma 4 suggests, imposing a higher service fee on rejections leads to a higher acceptance rate and lower compensation for crowdworkers. These factors introduce complex dynamics into the platform's utility. For instance, lower compensation might diminish the incentive for crowdworkers to submit high-quality work, subsequently reducing the requester's utility. Consequently, the platform cannot set excessively high c_1 and c_2 without risking the requester's exit from the market. Moreover, a higher acceptance rate yields mixed effects on the platform's utility. While it decreases the need to recruit many crowdworkers and reduces the number of rejections, which lowers both the reputation loss and the recruitment cost, it also diminishes revenue derived from service fees on rejected submissions. These intricate effects underscore the need for a carefully considered service fee structure. To deepen our understanding of the decisions made by the platform and the requester, we analyze the equilibrium of the game in the following lemma.

Lemma 6. *(Equilibrium Analysis) The equilibrium of the requester and the platform is given as follows*

1. *If* $h + r < \frac{\bar{s}}{4}$ *and* $h \leq \frac{(a+r)^2}{\bar{s}} + \frac{a-r}{2} + \frac{\bar{s}}{16}$*, the platform sets* $c_1^* = a + h + r - \sqrt{\bar{s}(h+r)} + \frac{\bar{s}}{4}$ *and* $c_2^* = h + r$*. Correspondingly, the requester chooses* $\pi^* = \frac{2\sqrt{h+r}}{\sqrt{\bar{s}}}$ *and* $w^* = \frac{\bar{s} - 2\sqrt{\bar{s}(h+r)}}{4}$*. The platform and the requester obtain* $EU^P = \frac{m(4a - 4\sqrt{\bar{s}(h+r)} + 4r + \bar{s})}{4}$ *and* $EU^R = 0$*, respectively.*
2. *If* $h + r \geq \frac{\bar{s}}{4}$ *and* $h \leq a$*, the platform sets* $c_1^* = a$ *and* $c_2^* \geq \frac{\bar{s}}{4}$*. The requester chooses* $\pi^* = 1$ *and* $w^* = 0$*. The platform and the requester obtain* $EU^P = m(a - h)$ *and* $EU^R = 0$*, respectively.*
3. *In other cases, the platform is unable to obtain nonnegative utility. Hence, the platform would not accept the requester's task.*

This lemma delineates three distinct scenarios that influence the strategic decisions of both the platform and the requester. In the first scenario, where both the recruitment cost and the reputation loss are low, the platform sets a low service fee for rejected submissions. Consequently, the requester chooses an acceptance rate below one to exploit the low cost of rejection. This fee structure serves a dual purpose: it compensates for the recruitment costs and the reputation loss associated with rejected crowdworkers, and it strategically encourages the use of rejection. In the second scenario, characterized by significant reputation loss from rejection, the platform imposes a higher fee on rejections to offset this loss. The increase in rejection cost discourages the requester from using the rejection design, leading to a strategy of universal acceptance to circumvent this cost. In the final scenario, when both the recruitment cost and the reputation loss are high, the platform is unable to establish service fees that maintain nonnegative utilities for both itself and the requester. Consequently, neither party enters the market.

Figure 7 (Color online) Effects of Reputation Loss and Hiring Cost on the Adoption of Rejection Design



Note. (a) $a = 0$, $\bar{s} = 8$; (b) $a = 1$, $\bar{s} = 8$; (c) $a = 2$, $\bar{s} = 8$.

Figure 7 illustrates optimal strategies across scenarios characterized by varying levels of the ability range ($\bar{s}$) and the quality-invariant utility derived from each accepted submission (a). The figure highlights regions in which the adoption of the rejection design is optimal, which locates in the bottom-left corner where both reputation loss and recruitment cost are relatively low. As reputation loss increases beyond a certain threshold, the optimal strategy transitions to a scenario where rejection is not utilized and hence rejection-related cost is eliminated. In this scenario, the platform's primary challenge shifts to identifying a feasible pricing strategy capable of covering recruitment costs. Consequently, the boundary separating the no-entry scenario (red area) and the scenario without rejection (blue area) emerges as a clearly defined straight line. Beyond this line, the platform can no longer sufficiently cover its recruitment cost. In contrast, the boundary delineating the scenario that employs rejection (blue area) and the no-entry scenario lies slightly higher than this straight line. This difference indicates that the rejection design enables the platform to capture additional surplus, thus increasing its capacity to absorb higher recruitment cost. In other words, the implementation of the rejection design provides platforms with greater flexibility against cost fluctuations.

This visualization, in conjunction with Lemma 6, further reveals two critical insights regarding the equilibrium dynamics under different values of $\bar{s}$ and a. First, a higher quality-invariant benefit a enables the platform to leverage its first-mover advantage to extract more revenue from the requester, thus facilitating market entry even with heightened recruitment cost and reputation loss. This effect is evidenced by the upward shift in the upper boundaries of the blue and green areas in the figure. Second, when the task demands higher abilities, the platform is more likely to encourage rejection despite higher associated reputation loss, because higher-ability crowdworkers produce superior submissions when motivated by the rejection design. This dynamic allows the requester to bear a higher rejection fee, which allows the platform to cover more costs. This relationship is depicted by the rightward expansion of the blue area in the figure.

4.4. The Impact of Rejection Design on Each Party's Welfare: Win-Win-Win

To further evaluate the impact of the rejection design on the welfare of all parties, we derive the following propositions.

PROPOSITION 5. *(Platform Welfare) The rejection design generates higher platform welfare compared to the scenario of universal acceptance.*

As the first mover, the platform can leverage the service fee c_2 to influence the requester's decision on whether to employ rejection. Consequently, the platform is guaranteed not to be worse off compared to a scenario without a rejection design. Surprisingly, however, the rejection design actually enhances the platform's welfare. This increase is primarily because the rejection design enables the requester to derive a higher surplus from submission quality. It is important to note that the requester's welfare remains unchanged as the platform consistently uses its first-mover advantage to maximize its benefits, which is often at the expense of the requester's welfare. However, the requester still benefits from improved submission quality.

PROPOSITION 6. *(Crowdworker Welfare) The rejection design generates higher overall crowdworker welfare compared to the scenario of universal acceptance.*

This proposition may seem counterintuitive at first. Common reasoning might suggest that rejection would disadvantage crowdworkers, as those with rejected submissions incur costs without compensation. However, our analysis reveals that overall crowdworker welfare actually increases under the rejection design. The underlying mechanism is that the risk of being rejected motivates crowdworkers to exert more effort, competing for the chance to have their submissions accepted. Consequently, the requester is inclined to offer higher compensation to encourage superior submission quality. This dynamic effectively eliminates the problem where "bad money drives out good". As a result, more capable crowdworkers benefit from higher surpluses, while less capable crowdworkers who exerting minimal effort, experience only marginal changes in their surplus.

Propositions 5 and 6 together underscore the effectiveness of the rejection design over scenarios where rejection is not an option. In addition to its efficiency on promoting increased effort among capable crowdworkers (Proposition 1) and approximating the theoretical full information benchmark in large sample (Proposition 4), the rejection design also significantly enhances social welfare. First, it boosts the welfare of both the crowdworkers and the platform. Second, although it does not incluence the requester's welfare, it enhances the quality of submissions in the crowdsourcing task. These benefits explain the phenomenon that many leading crowdsourcing platforms have adopted the rejection design.

5. Discussions

In this section, we examine two alternative scenarios. In practice, many crowdsourcing platforms set a fixed minimum acceptance rate for all tasks and provide full refunds for rejected submissions. We explore this scenario in subsection 5.1. Furthermore, we explore the first-best scenario in which the platform and the requester are integrated in subsection 5.2.

5.1. The Common Practice Scenario: a Minimum Acceptance Rate

In practice, many crowdsourcing firms specify a minimum acceptance rate and refund the requester for rejected submissions, so the requester does not incur any cost for the rejected submissions. In our rejection design, we allow the requester to decide the acceptance rate without any restriction, while the platform influences the requester's decision by charging a fee for the rejected submissions. In the following proposition, we compare our rejection design with this common practice.

Proposition 7. *(Fee-Based Rejection Design V.S. Minimum Acceptance Rate Enforced Rejection Design) Influencing the acceptance rate through pricing/fees yields greater benefits for the platform than imposing a fixed minimum acceptance rate and providing a full refund for rejected submissions.*

While many crowdsourcing platforms commonly implement a fixed minimum acceptance rate and offer full refunds for rejected submissions, we argue that this mechanism is suboptimal. The dominant strategy for the requester, in this case, is to consistently adhere to the minimum acceptance rate. This fosters free-riding behavior as it allows requesters to incentivize higher submission quality through rejection without incurring any costs. As a result, the platform is left unable to cover the recruitment cost and the reputation loss associated with rejected crowdworkers. In contrast, by imposing a service fee on rejected submissions, the platform can transfer these costs to the requester, effectively aligning the cost of each task with its underlying recruitment and reputational risks. An implication of this approach is the important role of c_2, the service fee on rejections, in rebalancing the power dynamics between the platform and the requester. The platform can not only generate additional revenue through this fee, but also use it as a strategic deterrent against excessive or unwarranted use of rejection, which helps the platform mitigate the reputational harm that may arise from perceived unfair treatment of crowdworkers.

5.2. The First Best Scenario: System Integration

In this section, we explore a first-best scenario where the platform and the requester operate as a fully integrated entity, henceforth referred to as the integrated platform. Such integration implies that all transaction costs, if present, are internalized, which removes potential inefficiencies caused by separate decision-making processes. In this idealized setting, the integrated platform's decision variables are limited to determining the optimal acceptance rate π and the appropriate compensation w for crowdworkers. The expected utility for the integrated platform, denoted as EU^I, is expressed as follows:

$$EU^I = \underbrace{ma + m\sqrt{w\bar{s}(1-\pi)}}_{\text{utility from submissions}} - \underbrace{mw}_{\text{compensation}} - \underbrace{\frac{m}{\pi}(1-\pi)r}_{\text{reputation loss}} - \underbrace{\frac{m}{\pi}h}_{\text{hiring cost}} .$$

We solve for the best response for the integrated platform in the following lemma.

Lemma 7. *(Equilibrium Analysis in the First-Best Scenario) The best response of the integrated platform is given as follows*

1. *If* $h + r < \frac{\bar{s}}{4}$ *and* $h \leq \frac{(a+r)^2}{\bar{s}} + \frac{a-r}{2} + \frac{\bar{s}}{16}$, *the integrated platform sets* $\pi^* = \frac{2\sqrt{h+r}}{\sqrt{\bar{s}}}$ *and* $w^* = \frac{\bar{s}-2\sqrt{\bar{s}(h+r)}}{4}$. *Its expected utility is* $EU^I = \frac{m(4a-4\sqrt{\bar{s}(h+r)}+4r+\bar{s})}{4}$.
2. *If* $h + r \geq \frac{\bar{s}}{4}$ *and* $h \leq a$, *the integrated platform sets* $\pi^* = 1$ *and* $w^* = 0$. *Its expected utility is* $EU^I = m(a-h)$.
3. *In other cases, the integrated platform is unable to obtain nonnegative utility. Hence, the platform would not enter the market.*

Analogous to our main model, this first-best setting delineates three distinct equilibria, determined by varying degrees of reputation loss and recruitment cost. Interestingly, we observe that the equilibrium outcomes in this first-best scenario coincide precisely with the requester's equilibrium decisions described earlier in Lemma 6. We formalize this surprising finding in the following proposition.

PROPOSITION 8. *(Coordination) Fee-based rejection design can coordinate the platform and requester to achieve the first best performance.*

Proposition 8 reveals an insightful and somewhat counterintuitive finding. It shows that the rejection design through enforcing a fee for rejected submissions can coordinate the system, yielding identical utility and decisions for all involved parties, irrespective of whether the platform and the requester act independently or as an integrated entity. Both the independent and integrated setups lead to the same acceptance rate and crowdworker compensation. This equivalence arises because both players, if possible, employ rejection strategically to incentivize crowdworkers to exert greater effort. The requester benefits directly from improved submission quality, while the platform simultaneously benefits by capturing a larger portion of the requester's surplus. Thus, their incentives regarding acceptance decisions align under this rejection design.

Propositions 7 and 8 offer guidance for the design of crowdsourcing platforms. Rather than mandating a minimum acceptance rate, as is commonly practiced, platforms should grant requesters full discretion in setting their own acceptance thresholds. At the same time, platforms can guide these decisions by implementing a service fee for rejected submissions. This rejection-based pricing mechanism not only discourages misuse but also enables platforms to achieve first-best performance.

6. Managerial Implication

Our findings offer valuable insights and practical implications for both requesters and crowdsourcing platforms, highlighting opportunities to enhance effectiveness, efficiency, and profitability through strategic implementation of the rejection design.

Managerial Implications for Requesters. Our analysis demonstrates that implementing a rejection design effectively motivates high-ability crowdworkers to invest more effort, which significantly improves the quality of submissions. Specifically, when the crowdworker pool is sufficiently large, the rejection design approximates the optimal outcomes achievable under full information scenarios. Therefore, requesters can strategically utilize rejection as a mechanism to communicate quality expectations implicitly and to incentivize participants to deliver higher-quality submissions. By carefully selecting acceptance rates and providing appropriate compensation, requesters can balance submission quality and costs, ultimately achieving superior crowdsourcing outcomes.

Managerial Implications for Crowdsourcing Platforms. Our results also have direct implications for crowdsourcing platforms, particularly in terms of pricing/fee strategy. Traditional practices on major platforms typically involve establishing fixed minimum acceptance rates and issuing full refunds for rejected submissions. However, our analysis reveals this approach to be suboptimal, as it fails to adequately cover recruitment and reputation-related costs incurred by the platform. Instead, we recommend that platforms remove any restriction on the acceptance rate and incorporate a service fee for rejected submissions. This approach not only compensates platforms for the costs associated with rejected submissions but also discourages requesters from excessive or unjustified rejection, promoting healthier market behavior.

Moreover, we find that the rejection design positively affects overall crowdworker welfare, an outcome that supports the adoption of this approach by platforms. By enhancing crowdworker satisfaction and motivating higher-quality submissions, platforms can cultivate a more engaged and productive workforce. This, in turn, fosters sustainability and profitability. Thus, our findings advocate for platforms to embrace and refine rejection-based pricing strategies and align their operational practices with the broader objectives of stakeholder satisfaction and market efficiency.

7. Conclusion

This paper explores the rejection design on crowdsourcing platforms. While multiple quality control methods within these platforms have been examined, the rejection design has received surprisingly little attention in academic literature. In practice, while many major crowdsourcing platforms have adopted this design, the policies governing its use vary significantly, highlighting a lack of consistent understanding regarding its application. In this paper, we develop a model that captures the dynamics between crowdworkers, the requester, and the platform. We employ an auction framework to analyze the actions of crowdworkers when confronted with the possibility of being rejected. Building on this, we further explore the equilibrium between the requester and the platform across various scenarios. Our theoretical insights provide a foundational understanding of business practices on crowdsourcing platforms and offer strategic guidance for developing pricing strategies tailored to different crowdsourcing scenarios.

First, we assess the efficiency and optimality of the rejection design. Our analysis reveals that, when faced with the risk of rejection, higher-ability crowdworkers typically produce higher-quality submissions. Furthermore, we discover that, from the requesters' perspective, the optimality of the rejection design closely approaches the theoretical upper bound as the number of crowdworkers increases. This highlights its effectiveness in typical crowdsourcing settings that demand significant participation. Second, we explore the interaction between the platform and the requester. Our findings indicate that both the adoption and pricing strategies are shaped by the potential costs faced by the platform. We examine the optimal responses for both the requester and the platform across various scenarios. Third, we conduct a welfare analysis for all parties involved. Interestingly, we find that the rejection design creates a tripartite win-win-win situation for the platform, the requester, and the crowdworkers. Our results also show that the platform benefits more than either a no-rejection design or a zero-cost rejection policy. Moreover, our proposed rejection design coordinates the system to achieve the first-best performance as if the platform and the requester are integrated. These insights support a more nuanced implementation of the rejection design in practical applications.

Our study, while providing valuable insights into the rejection design within crowdsourcing platforms, is not without limitations, which present avenues for future research. First, our model does not account for a sequential context where players repeatedly make decisions over time. Investigating a more dynamic aspect of the rejection design could prove beneficial. For example, incorporating an individual reputation system (e.g., Goes et al. 2016) might reveal long-term effects of rejection on crowdworker engagement and performance. Additionally, exploring negotiation processes, such as allowing crowdworkers to resubmit rejected submissions, could further optimize the design's effectiveness and fairness. Second, our analysis is based on a monopoly scenario where a single platform operates without competition. Future research could enhance the model by considering competitive dynamics between multiple platforms (e.g. Stouras et al. 2025) and explore how platforms compete to attract and retain both crowdworkers and requesters. Third, our model does not account for the moral hazard where the requester may reject a submission on the platform yet still utilize it in downstream tasks. Fourth, the potential for crowdworker learning within community-driven platforms presents another rich area for study. Many crowdsourcing platforms operate communities where crowdworkers can share insights and strategies. Understanding how this communal learning affects individual and collective performance could provide deeper insights into task engagement and quality.

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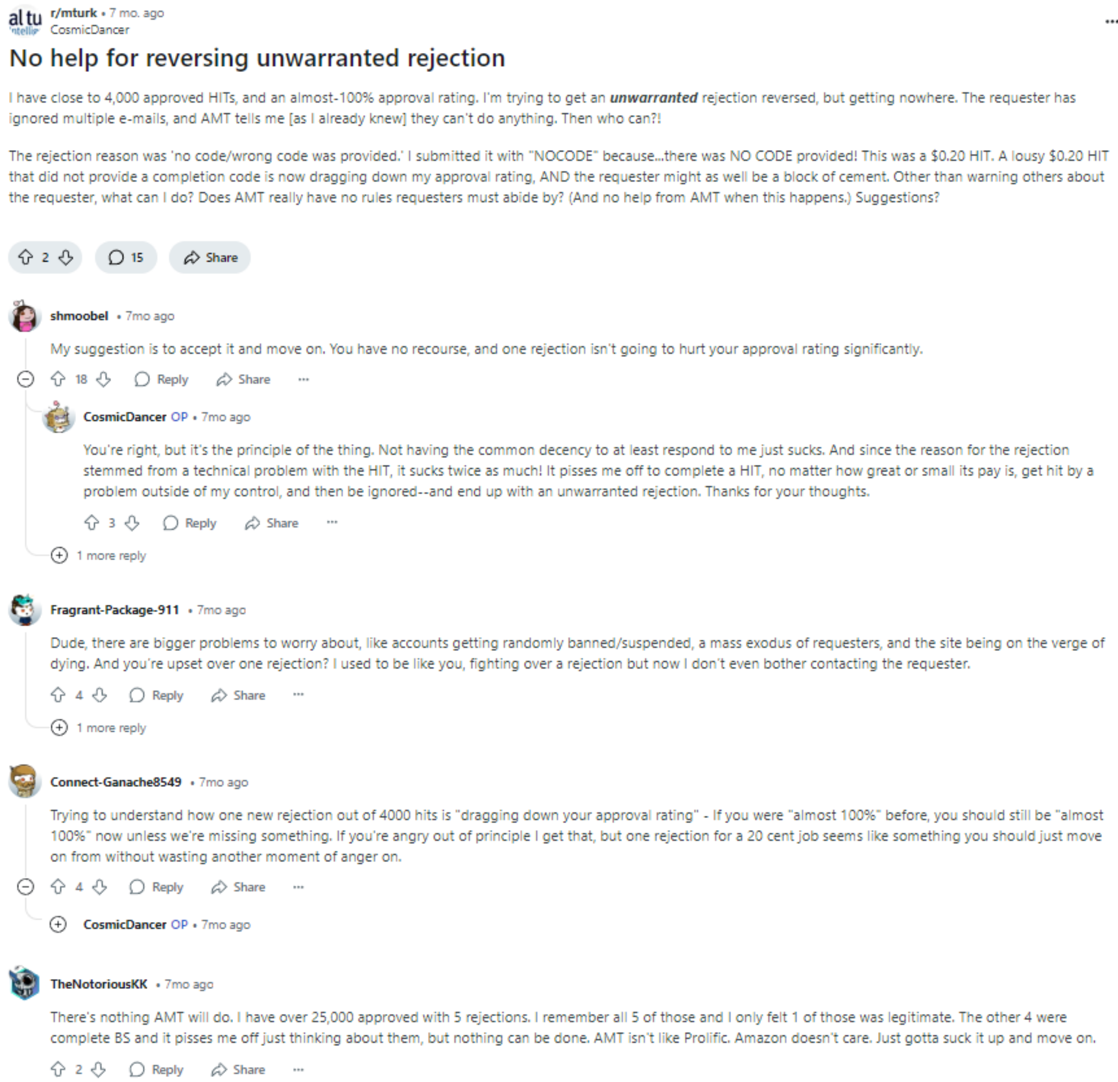
Online Appendix A: Figures

Figure A.1 An Example of Crowdworker Complaint Regarding Rejection



Note. This figure illustrates an example of reputation loss due to rejection on Amazon Mechanical Turk. Source: Reddit (https://www.reddit.com/r/mturk/comments/1fbea47/no_help_for_reversing_unwarranted_rejection/). Accessed on April 4, 2025.

Online Appendix B: Additional Lemmas

LEMMA B.1. *The rejection design is efficient, as it encourages higher-ability crowdworkers to submit higher-quality work (i.e., $\frac{dq_i}{ds_i} > 0$).*

Proof. Denote $F(\cdot)$ as the cumulative distribution function (CDF) of s_i and $f(\cdot)$ as the probability density function (PDF). Let $g_m(\cdot)$ and $G_m(\cdot)$ denote the PDF and CDF of the m-th highest s_i among $n-1$ crowdworkers, respectively. Let EU_i^C denote the expected utility for crowdworker i. Hence, we have

$$EU_i^C = \left(w - \frac{q_i}{s_i}\right)\mathbb{P}(q_i > q_{-i,m}) - \frac{q_i}{s_i}\mathbb{P}(q_i < q_{-i,m}) = wG_m(\eta^{-1}(q_i)) - \frac{q_i}{s_i},$$

where $q_i = \eta(s_i)$ represents crowdworker i' optimal response given his type s_i. We focus on symmetric equilibrium in which each crowdworker chooses submission quality to maximize his expected utility. We have

$$\begin{aligned} \frac{dEU_i^C}{dq_i} &= \frac{w\,[G_m(s_i)]'}{\eta'(s_i)} - \frac{1}{s_i}, \\ \frac{dEU_i^C}{dq_i} &= 0 \Rightarrow \eta'(s_i) = w s_i g_m(s_i) > 0. \end{aligned} \tag{B.1}$$

The lemma is proved.

Lemma B.2. *Consider $(X_1, ..., X_n)$ as n independent and identically distributed samples drawn from a distribution with a known CDF $F(x)$. Let X_m denote the m-th highest value among these samples. Then, X_m converges to $F^{-1}(\pi)$ in probability as n approaches infinity, where $\pi = \frac{m}{n}$.*

Proof. Define the empirical CDF $F_n(x) = \frac{1}{n}\sum_{i=1}^{n} 1_{[X_i \le x]}$. We have

$$\begin{aligned} \mathbb{P}(X_m - F^{-1}(\pi) > \epsilon) &= \mathbb{P}(F^{-1}(\pi) + \epsilon < X_m) \\ &= \mathbb{P}(F_n(F^{-1}(\pi) + \epsilon) < \pi) \\ &= \mathbb{P}(F_n(F^{-1}(\pi) + \epsilon) - F(F^{-1}(\pi) + \epsilon) < \pi - F_n(F^{-1}(\pi) + \epsilon)) \end{aligned}$$

Since $\pi - F(F^{-1}(\pi) + \epsilon) < \pi - F(F^{-1}(\pi)) = 0$, there exists a δ such that $\pi - F(F^{-1}(\pi) + \epsilon) < -\delta$. By Strong Law of Large Numbers, $F_n(x)$ converges to $F(x)$ almost surely. Hence, when $n \to \infty$, we have

$$\begin{aligned} &\mathbb{P}(F_n(F^{-1}(\pi) + \epsilon) - F(F^{-1}(\pi) + \epsilon) < \pi - F_n(F^{-1}(\pi) + \epsilon)) \\ \le\; &\mathbb{P}(F_n(F^{-1}(\pi) + \epsilon) - F(F^{-1}(\pi) + \epsilon) < -\delta) \to 0 \end{aligned}$$

Similarly, we have $\mathbb{P}(X_m - F^{-1}(\pi) < -\epsilon) \to 0$ when $n \to \infty$.

Lemma B.3. $\int_0^1 \sqrt{I_x((1-\pi)n+1, \pi n)}\, I_x((1-\pi)n, \pi n)dx < \pi$.

Proof. Since $I_x((1-\pi)n+1, \pi n) \in [0,1]$ and $I_x((1-\pi)n, \pi n) \in [0,1]$, by Cauchy–Schwarz inequality, we have

$$\begin{aligned} &\int_0^1 \sqrt{I_x((1-\pi)n+1, \pi n)}\, I_x((1-\pi)n, \pi n)dx \\ \le\; &\left(\int_0^1 I_x((1-\pi)n+1, \pi n)dx \int_0^1 I_x^2((1-\pi)n, \pi n)dx\right)^{\frac{1}{2}} \\ \le\; &\left(\int_0^1 I_x((1-\pi)n+1, \pi n)dx \int_0^1 I_x((1-\pi)n, \pi n)dx\right)^{\frac{1}{2}} \\ =\; &\left(\frac{\mathrm{Beta}((1-\pi)n+1, \pi n+1)}{\mathrm{Beta}((1-\pi)n+1, \pi n)} \frac{\mathrm{Beta}((1-\pi)n, \pi n+1)}{\mathrm{Beta}((1-\pi)n, \pi n)}\right)^{\frac{1}{2}} \\ =\; &\pi \left(\frac{n}{n+1}\right)^{\frac{1}{2}} \\ <\; &\pi. \end{aligned}$$

Lemma B.4. $\lim_{n\to\infty} \int_0^1 \sqrt{I_x((1-\pi)n+1, \pi n)}\, I_x((1-\pi)n, \pi n)dx = \pi$.

Proof. Consider a random draw of $x \in [0,1]$ from the distribution with a CDF of $I_x((1-\pi)n+1, \pi n)$. The mean and variance of x are respectively given by

$$\mathbb{E}[x] = \frac{(1-\pi)n+1}{n+1}, \ \mathrm{Var}(x) = \mathbb{E}\left[(x-\mathbb{E}[x])^2\right] = \frac{\pi n[(1-\pi)n+1]}{(n+1)^2(n+2)}.$$

By Chebyshev's inequality, we have

$$\mathbb{P}\left(\left|x - \frac{(1-\pi)n+1}{n+1}\right| \geq b\right) \leq \frac{\pi n[(1-\pi)n+1]}{b^2(n+1)^2(n+2)}. \tag{B.2}$$

Let $b = b(n) = n^{\beta}$, where $\beta \in (-\frac{1}{2}, 0)$. The RHS of the equation decreases in n and goes to zero when $n \to \infty$. For $x = 1-\pi+\Delta\pi$, where $\Delta\pi \in \mathbb{R} \setminus \{0\}$ is a constant, there exists $n \geq \left|\Delta\pi - \frac{\pi}{n+1}\right|^{1/\beta}$ that ensures $\left|x - \frac{(1-\pi)n+1}{n+1}\right| \geq b$. Hence, by taking $n \to \infty$, we have $\mathbb{P}(x \neq 1-\pi) \to 0$ and $\mathbb{P}(x = 1-\pi) \to 1$. Thus

$$\lim_{n\to\infty} I_x(\pi n, (1-\pi)n+1) = 1, \ x > 1-\pi,$$
$$\lim_{n\to\infty} I_x(\pi n, (1-\pi)n+1) = 0, \ x < 1-\pi.$$

Similar conclusions also apply to random variables drawn from another probability distribution with the CDF $I_x((1-\pi)n, \pi n)$. Hence, the lemma is proved.

Online Appendix C: Proof Details

Proof of Lemma 1. Since s_i follows a uniform distribution on $[0, \bar{s}]$, we denote $g_m(x)$ and $G_m(x)$ as the PDF and CDF of the m-th highest $\frac{s_i}{\bar{s}}$ among $n-1$ crowdworkers, respectively. We have

$$g_m(x) = (n-1)f(x)\binom{n-2}{m-1}[F(x)]^{n-m-1}[1-F(x)]^{m-1} = \frac{x^{n-m-1}(1-x)^{m-1}}{\mathrm{Beta}(n-m,m)},$$
$$G_m(x) = \int_0^x \frac{x^{n-m-1}(1-x)^{m-1}}{\mathrm{Beta}(n-m,m)}dx = \frac{\mathrm{Beta}_x(n-m,m)}{\mathrm{Beta}(n-m,m)} = I_x(n-m,m).$$

Using Equation B.1, the optimal response quality for crowdworker i becomes

$$\begin{aligned}\eta(s_i) &= w\bar{s}\int_0^{s_i/\bar{s}} \frac{x^{n-k}(1-x)^{k-1}}{\mathrm{Beta}(n-k,k)}dx + C \\ &= w\bar{s}\frac{\mathrm{Beta}(n-k+1,k)}{\mathrm{Beta}(n-k,k)}\int_0^{s_i/\bar{s}} \frac{x^{n-k}(1-x)^{k-1}}{\mathrm{Beta}(n-k+1,k)}dx + C \\ &= w\bar{s}(1-\pi)I_{s_i/\bar{s}}((1-\pi)n+1, \pi n) + C.\end{aligned}$$

Since $EU_i^C = 0$ when $s_i = 0$, we have $C = 0$. The lemma is proved.

Proof of Propositions 1 and 2. Trivial, omitted.

Proof of Proposition 3. Lemma B.4 shows that $\lim_{n\to\infty} I_x(\pi n, (1-\pi)n+1) = 1$ if $x > 1-\pi$, while $\lim_{n\to\infty} I_x(\pi n, (1-\pi)n+1) = 0$ if $x < 1-\pi$. This proves the proposition.

Proof of Lemma 2.

$$\begin{aligned}EU^R &= \mathbb{E}\left[\sum_{i=1}^{n} EU_i^R\right] \\ &= n\int_0^{\bar{s}} \Big[(\sqrt{q_i} + a - w - c1)G_m(s) - c_2(1-G_m(s))\Big]ds \\ &= n\sqrt{w\bar{s}(1-\pi)}\int_0^1 \sqrt{I_x((1-\pi)n+1,\pi n)}I_x((1-\pi)n,\pi n)dx + n\frac{m}{n}a - n\frac{m}{n}c_1 - n\frac{n-m}{n}c_2 \\ &= \frac{m}{\pi}\sqrt{w\bar{s}(1-\pi)}\int_0^1 \sqrt{I_x((1-\pi)\frac{m}{\pi}+1,m)I_x((1-\pi)\frac{m}{\pi},m)}dx + ma - mc_1 - \frac{m}{\pi}(1-\pi)c_2.\end{aligned}$$

Proof of Lemma 3. If all crowdworkers can observe each other's type, those with $s \geq s^m$ will choose for a submission quality of $q = ws^m$ to ensure acceptance, while the rest will adopt zero quality as their best responses. Hence, the requester's expected total utility from submission quality is $\mathbb{E}[m\sqrt{q}] \leq m\sqrt{\mathbb{E}[q]} = \sqrt{m\bar{s}(1-\pi)}$. Lemma B.2 shows that $\mathbb{E}[m\sqrt{q}] \to \sqrt{m\bar{s}(1-\pi)}$ when $n \to \infty$.

Proof of Proposition 4. Since $n = \frac{m}{\pi}$, we have

$$Q = \frac{m}{\pi}\sqrt{w\bar{s}(1-\pi)}\int_0^1 \sqrt{I_x\left((1-\pi)n+1, \pi n\right) I_x\left((1-\pi)n, \pi n\right)}\, dx.$$

Lemmas B.3 and B.4 show that $Q < m\sqrt{w\bar{s}(1-\pi)}$ and $\lim_{n\to\infty} Q \to m\sqrt{w\bar{s}(1-\pi)}$. Hence, we have $\tau < 1$ and $\lim_{n\to\infty} \tau \to 1$.

Proof of Lemma 4. First, consider the scenario where $\pi \in (0,1)$. Solving the first-order conditions (FOC) for the expected utility of the requester EU^R with respect to π and w, we find $\pi = \frac{2\sqrt{c_2}}{\sqrt{\bar{s}}}$ and $w = \frac{\bar{s}-2\sqrt{c_2\bar{s}}}{4}$. The second-order conditions (SOC) confirm that this solution maximizes EU^R. To ensure $\pi \in (0,1)$, it is required that $0 \leq c_2 < \frac{\bar{s}}{4}$. Conversely, if $c_2 \geq \frac{\bar{s}}{4}$, we have $\pi = 1$ and the requester and the requester minimizes costs by setting $w = 0$ to maximize EU^R.

Proof of Lemma 5.

$$\begin{aligned}
EU^P &= \mathbb{E}\left[\sum_{i=1}^{n} EU_i^P\right] \\
&= n\int_0^{\bar{s}} \Big[(c_1 - h)G_m(s) - (c_2 - h - r)(1 - G_m(s))\Big] ds \\
&= mc_1 + \frac{m}{\pi}(1-\pi)c_2 - \frac{m}{\pi}(1-\pi)r - \frac{m}{\pi}h.
\end{aligned}$$

Proof of Lemma 6 and Proposition 5. The platform sets the service fees, c_1 and c_2, to maximize its expected utility, subject to a constraint that ensures requester entry:

$$\max_{c_1, c_2} EU^P \text{ s.t. } EU^R \geq 0.$$

We first consider the scenario where $\pi \in (0,1)$. Using Lemma 4, we have $EU^R = m(a - c_1 + c_2 - \sqrt{c_2\bar{s}} + \frac{1}{4}\bar{s})$ and $EU^P = m(c_1 - c_2 + r) + \frac{m\sqrt{\bar{s}}(c_2-h-r)}{2\sqrt{c_2}}$. We define the Lagrangian for this optimization problem as:

$$L(c_1, c_2, \lambda) = m(c_1 - c_2 + r) + \frac{m\sqrt{\bar{s}}(c_2 - h - r)}{2\sqrt{c_2}} + \lambda\left(a - c_1 + c_2 - \sqrt{c_2\bar{s}} + \frac{1}{4}\bar{s}\right).$$

To find the optimal service fees, we apply the Karush-Kuhn-Tucker (KKT) conditions:

- Stationarity: $m - \lambda = 0$ and $\frac{1}{4}n(\frac{\sqrt{\bar{s}}(c_2+h+r)}{c_2^{3/2}} - 4) - \frac{\lambda\sqrt{\bar{s}}}{2\sqrt{c_2}} + \lambda = 0$.
- Primal feasibility: $a - c_1 + c_2 - \sqrt{c_2\bar{s}} + \frac{1}{4}\bar{s} \geq 0$.
- Dual feasibility: $\lambda \geq 0$.
- Complementary slackness: $\lambda(a - c_1 + c_2 - \sqrt{c_2\bar{s}} + \frac{1}{4}\bar{s}) = 0$.

From these conditions, we find the solutions: $c_1^* = a + h + r - \sqrt{(h+r)\bar{s}} + \frac{1}{4}\bar{s}$ and $c_2^* = h + r$. As a result, the requester obtains $EU^R = 0$ and the platform obtains $EU^P = \frac{m(4a - 4\sqrt{(h+r)\bar{s}} + 4r + \bar{s})}{4}$. The platform will enter the market if and only if it can achieve nonnegative utility, i.e., $EU^P \geq 0$. This condition implies that $h \leq \frac{(a+r)^2}{\bar{s}} + \frac{a-r}{2} + \frac{\bar{s}}{16}$. The use of rejection requires $c_2 < \frac{\bar{s}}{4}$. This case also requires $h < \frac{\bar{s}}{4} - r$.

Next, we consider the scenario where $\pi = 1$. In this case, we have $EU^R = m(a - c_1)$ and $EU^P = m(c_1 - h)$. Hence, the platform chooses $c_1 = a$ and $c_2 \geq \frac{\bar{s}}{4}$. Thus, the requester obtains $EU^R = 0$ and the platform obtains $EU^P = m(a-h)$. This equilibrium is achieved when $h \leq a$ and $h \geq \frac{\bar{s}}{4} - r$.

To ensure that when $h < \frac{\bar{s}}{4} - r$, the platform will choose for a $c_2 < \frac{\bar{s}}{4}$ to encourage rejection, we conduct a final check. The difference in utility between the two cases is given by:

$$\frac{m(4a - 4\sqrt{(h+r)\bar{s}} + 4r + \bar{s})}{4} - m(a-h) = \frac{m}{4}(\sqrt{\bar{s}} - 2\sqrt{h+r})^2 > 0.$$

This means that encouraging rejection is a dominant strategy for the platform when $h < \frac{\bar{s}}{4} - r$.

Proof of Proposition 6. Let EU^C denote the average utility for all crowdworkers. Lemma 6 shows that when the rejection design is not used, the requester sets the compensation at $w = 1$, leading to $EU^C = 0$. Now, consider that the requester uses the rejection design, we have

$$\begin{aligned}
EU^C &= \int_0^{\bar{s}} wG_m(s) - \frac{\eta(s)}{s} ds \\
&= w\bar{s}\pi - w\bar{s}(1-\pi) \int_0^1 \frac{I_x((1-\pi)n+1, \pi n))}{x} dx \\
&= w\bar{s}\pi - w\bar{s}(1-\pi) \left[[I_x((1-\pi)n+1, \pi n)) \log(x)]_0^1 - \int_0^1 \frac{x^{(1-\pi)n}(1-x)^{\pi n - 1}}{\text{Beta}((1-\pi)n+1, \pi n)} \log(x) dx \right] \\
&= w\bar{s}\pi - w\bar{s}(1-\pi) \int_0^1 \frac{x^{(1-\pi)n}(1-x)^{\pi n - 1}}{\text{Beta}((1-\pi)n+1, \pi n)} (-\log(x)) dx \\
&= w\bar{s}\pi - w\bar{s}(1-\pi) \left[\psi_0(n+1) - \psi_0((1-\pi)n+1)\right] \\
&= w\bar{s}\pi - w\bar{s}(1-\pi) \left[H_n - H_{(1-\pi)n}\right] \\
&\geq w\bar{s} \left[\pi + (1-\pi)\log(1-\pi)\right].
\end{aligned}$$

Here, ψ_0 denotes the digamma function, and H_n denotes the the n-th harmonic number. It is trivial to show that $\pi + (1-\pi)\log(1-\pi) > 0 \; \forall \pi \in (0,1)$.

Proof of Proposition 7. We consider a different setting of the game. That is, instead of imposing a minimum acceptance rate, the platform directly determines a customized acceptance rate for each requester and does not charge any fee to the requester for the rejected submissions. Hence, the requester maximizes:

$$EU^R = \underbrace{ma + m\sqrt{w\bar{s}(1-\pi)}}_{\text{utility from submissions}} - \underbrace{mw}_{\text{compensation}} - \underbrace{mc_1}_{\text{platform service fee}}.$$

The expected utility of the platform is expressed as:

$$EU^P = \underbrace{mc_1}_{\text{platform service fee}} - \underbrace{\frac{m}{\pi}(1-\pi)r}_{\text{reputation loss}} - \underbrace{\frac{m}{\pi}h}_{\text{hiring cost}}.$$

The FOC and SOC suggest that $w = \frac{(1-\pi)\bar{s}}{4}$ maximizes the requester's utility. The platform chooses c_1 and π to solve the following optimization problem:

$$\max_{c_1, \pi} EU^P \text{ s.t. } EU^R \geq 0.$$

We define the Lagrangian for this optimization problem as:

$$L(c_1, \pi, \lambda_1, \lambda_2) = \frac{m(\pi c_1 + \pi r - h - r)}{\pi} + \lambda_1 \left(a - c_1 + \frac{(1-\pi)\bar{s}}{4} \right) + \lambda_2(1-\pi).$$

We apply the KKT conditions:

- Stationarity: $m-\lambda_1=0$ and $\frac{m(h+r)}{\pi^2}-\frac{\lambda_1\bar{s}}{4}-\lambda_2=0$.
- Primal feasibility: $a-c_1+\frac{(1-\pi)\bar{s}}{4}\geq 0$ and $1-\pi\geq 0$.
- Dual feasibility: $\lambda_1\geq 0$ and $\lambda_2\geq 0$.
- Complementary slackness: $\lambda_1(a-c_1+\frac{(1-\pi)\bar{s}}{4})=0$ and $\lambda_2(1-\pi)=0$.

Hence, we have $\pi^*=\sqrt{\frac{4m(h+r)}{m\bar{s}+4\lambda_2}}$. If $\lambda_2=0$, we have $\pi^*<0$. This requires that $h+r<\frac{\bar{s}}{4}$. In this case, $c_1^*=\frac{4a-2\sqrt{\bar{s}(h+r)}+\bar{s}}{4}$. The platform and the requester obtains $EU^P=\frac{m(4a-4\sqrt{\bar{s}(h+r)}+4r+\bar{s})}{4}$ and $EU^R=0$, respectively. Similar to Lemma 6, we need $h\leq\frac{(a+r)^2}{\bar{s}}+\frac{a-r}{2}+\frac{\bar{s}}{16}$ in this case. If $h+r\geq\frac{\bar{s}}{4}$, we have $\lambda_2=\frac{4m(h+r)-m\bar{s}}{4}\neq 0$ and $\pi^*=1$. In this case, $c_1^*=a$. The platform and the requester obtains $EU^P=m(a-h)$ and $EU^R=0$, respectively. This proposition can be directly drawn from these results. In scenarios where the platform sets the acceptance rate and offers full refunds for rejected submissions, the decision on π remains consistent with scenarios in which the requester determines the acceptance rate while the platform sets the pricing for rejections. Hence, a fixed π is not optimal.

Proof of Lemma 7. Trivial, omitted.

Proof of Proposition 8. Trivial, omitted.