Strategic Information Revelation in Crowdsourcing Systems Without Verification

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Abstract—We study a crowdsourcing problem where the platform aims to incentivize distributed workers to provide high-quality and truthful solutions without the ability to verify the solutions. While most prior work assumes that the platform and workers have symmetric information, we study an asymmetric information scenario where the platform has informational advantages. Specifically, the platform knows more information regarding workers’ average solution accuracy, and can strategically reveal such information to workers. Workers will utilize the announced information to determine the likelihood that they obtain a reward if exerting effort on the task. We study two types of workers: (1) **naive** workers who fully trust the announcement, and (2) **strategic** workers who update prior belief based on the announcement. For naive workers, we show that the platform should always announce a high average accuracy to maximize its payoff. However, this is not always optimal for strategic workers, as it may reduce the credibility of the platform’s announcement and hence reduce the platform’s payoff. Interestingly, the platform may have an incentive to even announce an average accuracy lower than the actual value when facing strategic workers. Another counter-intuitive result is that the platform’s payoff may decrease in the number of high-accuracy workers.

I. INTRODUCTION

A. Motivations

The rapid growth of the Internet has enabled crowdsourcing of various online tasks [1], [2]. Through appropriately assigning decomposed simple tasks to workers and effectively aggregating workers’ solutions, a crowdsourcing platform can manage to solve the original complex problem [3]. For example, Waze invites workers to report local traffic information and uses the reports to recommend driving routes [4]. Amazon Mechanical Turk recruits workers to do image labeling, and uses the collected labels to train machine learning models [5].

Even for a simple task, obtaining a high-quality solution requires a worker to exert enough effort. A platform needs to provide proper incentives to motivate this [6]. The design of incentives is particularly difficult when the platform cannot access the ground truth to verify the workers’ reported solutions.

For example, the ground truth can be costly to obtain (e.g., it is costly for Waze to judge the accuracy of the mobile workers’ reported traffic information, as it requires centralized managed sensors to validate all the submitted reports). This type of challenging crowdsourcing problem is known as information elicitation without verification (IEWV) [7].

Most IEWV literature (e.g., [8]–[12]) studied the problem as a game with symmetric information. The common assumption is that both the workers and the platform have the same information regarding the environment, e.g., worker capabilities. In many crowdsourcing platforms, however, information regarding the worker characteristics is asymmetric between the platform and workers. Usually, the platform has more information regarding worker characteristics through market research and past experiences. For example, in Amazon Mechanical Turk, each worker’s historical performance is known by the platform, but not by the other workers [5]. In this paper, we consider information asymmetry between the platform and the workers. As will be seen, such information asymmetry complicates the analysis of both the workers’ behaviors and the platform’s incentive design.

We apply the widely adopted majority voting scheme to solve the IEWV problem [13]–[15]. Specifically, a worker obtains a consistency reward if his solution matches the majority solution from the other workers. Besides the reward design under majority voting, we assume that the platform has one additional decision: information revelation. Specifically, we consider a mix of high and low accuracy workers, where the platform knows the number of each type (but the workers do not know). **We are particularly interested in studying whether the platform has an incentive to reveal this information to workers. Furthermore, we also want to study whether the platform may manipulate the revealed information, as truthful revelation may not benefit the platform or the workers** [16]–[19]. By analyzing the platform’s optimal information revelation decisions, we can understand how the platform takes advantage of this information asymmetry.

We model the interactions between the platform and the workers as follows (illustrated in Fig. 1):

1) **Stage I**: The platform decides the information revelation strategy.
2) **Stage II**: The platform decides the consistency reward under the majority voting scheme.
3) **Stage III**: The workers choose whether to exert effort finishing the task and whether to truthfully report solutions.

After workers finish the task and report their solutions in
Stage III, majority voting is implemented. Specifically, the platform collects the workers’ reported solutions and allocates consistency rewards to the workers whose solutions are consistent with the majority. Note that the majority voting’s results are directly determined by the previous three stages, and hence we do not treat it as a separate stage.

We study two types of workers: (1) naive workers who fully believe in the platform’s announcement, and (2) strategic workers who update their prior belief based on the announced information. The consideration of naive worker case serves as a benchmark and it can model the scenario where workers are confident in the platform’s announced information (especially for those platforms with good reputations). It can also model the scenario where workers have limited reasoning capabilities to deduce the authenticity of the announcement [20]. The consideration of strategic worker case, however, leads to more intriguing results. Such a consideration fits the scenario where workers do not trust the platform and where workers are strategic and have high reasoning capabilities [21]. As will be shown, the platform’s optimal information revelation strategies are very different when facing these two types of workers.

B. Key Contributions

The main contributions of this paper are as follows.

- **Studying strategic information revelation for the IEWV problem**: To the best of our knowledge, this is the first analytical work that studies strategic revelation of asymmetric information for the IEWV problem. The platform’s information revelation is a challenging non-convex problem, yet we can exploit its special structure to characterize the optimal solutions’ properties.

- **Characterizing workers’ equilibrium strategies**: We show that there are multiple equilibria among the workers. Under appropriate information revelation and reward design, it is a Pareto-dominant equilibrium for all the workers to exert effort and truthfully report their solutions.

- **Characterizing platform’s information revelation strategy**: We show that for naive workers, the platform should always announce a high average worker accuracy, independent of the actual information. However, this is not always optimal when facing strategic workers, as it may reduce the credibility of the platform’s announcement and hence reduce the platform’s payoff. When facing strategic workers, the platform may even have an incentive to announce an average accuracy lower than the actual value.

- **Performance evaluation**: We evaluate our mechanism via extensive numerical experiments. We show that the platform payoff increases in the workers’ prior belief regarding the number of high-accuracy workers. Surprisingly, the platform payoff may decrease in the number of high-accuracy workers. A larger number of these workers brings marginally decreasing benefits, but the cost required to incentivize them may grow significantly.

The remaining of the paper is organized as follows. In Section II, we review the related work. In Section III, we introduce the model. In Section IV, we provide complete analytical solutions to the model. We show numerical results in Section V and conclude in Section VI.

II. RELATED WORK

Our work studies strategic information revelation for IEWV. Hence, we review the related work from two aspects, i.e., the IEWV problem and strategic information revelation.

A. Information Elicitation Without Verification (IEWV)

IEWV is a canonical crowdsourcing problem where the platform cannot verify the workers’ reported solutions (e.g., [8], [22]–[24]). The key focus in IEWV is to design proper incentive mechanisms to encourage high-quality (and truthful) solutions. Miller et al. in [9] and Prelec et al. in [23] proposed peer prediction mechanisms to elicit truthful solutions from the workers. Dasgupta et al. in [25] and Liu et al. in [14] focused on designing mechanisms to induce workers’ effort exertion, which leads to high-quality solutions. Huang et al. in [15], [21] studied the impact of worker heterogeneity on the mechanism design for IEWV. However, these works did not consider information asymmetry and strategic information revelation between the platform and workers. Our work is the first analytical study to characterize the impact of strategic revelation of asymmetric information on the mechanism design for the IEWV problem.

B. Strategic Information Revelation

Strategic information revelation investigates how the players in a game strategically reveal and process information to maximize their payoffs [19], [26], [27]. Crawford et al. in [16] explored the famous cheap talk problem and characterized the optimal structures of revealed information that maximizes the sender’s payoff. Brocas et al. in [28] and Kamenica et al. in [18] studied the persuasion game considering costly information acquisition and revelation. However, these works
either made the strong assumption that the platform cannot lie [16] or that the information revelation is the only platform decision [18]. Different from these works, we consider a general model where the platform can choose to be honest or lying. Further, we jointly consider the platform’s strategic decisions on information revelation and reward design. Both the above considerations significantly complicate the analysis.

III. Model

In Section III-A, we introduce the workers’ decisions and payoffs. In Section III-B, we introduce the platform’s decisions and payoff, with an emphasis on the platform’s information revelation strategy.

A. Workers’ Decisions and Payoffs

In this subsection, we first introduce the task and workers, and then define each worker’s strategies and payoff function.

1) Task and Workers: A crowdsourcing platform aims to obtain solutions to a task via a set \( \mathcal{N} = \{1, 2, \ldots, N\} \) of workers. We consider a binary-solution task, e.g., judging whether the solution to an online math problem is Correct or Wrong. Let \( \mathcal{X} = \{0, 1\} \) denote the task’s solution space, where 1 means Correct and 0 means Wrong.\(^1\) and \( x \in \mathcal{X} \) is the task’s true solution that the platform does not know. After completing the task, each worker \( i \) generates an estimated solution \( x_{i_{\text{estimate}}} \in \mathcal{X} \), and he can report a value \( x_{i_{\text{report}}} \in \mathcal{X} \) to the platform that may or may not be the same as \( x_{i_{\text{estimate}}} \).

2) Worker Effort Exertion Strategy: Each worker can decide whether to exert effort doing the task, and the accuracy (i.e., quality) of his solution stochastically depends on his chosen effort level. Specifically, a worker can choose to either exert effort or not exert effort, and we use \( e_i \in \{0, 1\} \) to denote worker \( i \)’s effort level \([15], [21], [24]\). If worker \( i \) does not exert effort, i.e., \( e_i = 0 \), he will generate the correct solution (which is the task’s true solution) with probability 0.5 at zero cost. Here, we assume that without exerting effort a worker has no information about the true solution, so the estimated solution is equally likely to be correct or wrong \([15], [24]\).\(^2\) Exerting effort (i.e., \( e_i = 1 \)) improves a worker’s solution accuracy at a cost \( c \geq 0 \), and he can generate the correct solution with probability \( p_i \in (0, 0.5] \). More specifically,

\[
P_F(x_{i_{\text{estimate}}} = x) = \begin{cases} 0.5, & \text{if } e_i = 0 \text{ (with zero cost),} \\ p_i, & \text{if } e_i = 1 \text{ (with a cost } c \geq 0). \end{cases} \tag{1} \]

In this paper, we consider heterogeneous workers in which there are \( k \) out of \( N \) workers with a high accuracy level \( p_h \) and the remaining \( N - k \) workers have a low accuracy level \( p_l \), where \( 0 \leq k \leq N \) and \( 0.5 < p_l < p_h \leq 1 \). We use \( \mathcal{N}_h \) and \( \mathcal{N}_l \) to denote the set of high-accuracy and low-accuracy workers, respectively.

3) Worker Solution Reporting Strategy: Each worker also needs to decide whether to truthfully report his solution to the platform. For a worker \( i \) who does not exert effort, he can only apply the random reporting strategy denoted by \( r_i = \text{rd} \).\(^3\) For those workers who exert effort, they can either truthfully or untruthfully report their solutions, where we use \( r_i = \{1, -1\} \) to denote the reporting strategy with \( r_i = 1 \) indicating truthful reporting and \( r_i = -1 \) indicating untruthful reporting. More specifically,

\[
x_{i_{\text{report}}} = \begin{cases} x_{i_{\text{estimate}}}, & \text{if } r_i = 1, \\ -x_{i_{\text{estimate}}}, & \text{if } r_i = -1, \\ \epsilon \text{ or } -\epsilon \text{ with an equal probability}, & \text{if } r_i = \text{rd}. \end{cases} \tag{2} \]

In fact, workers can benefit from colluding to always report 1 (or -1) as the task solution, under the majority voting scheme. However, such colluding strategies require much coordination among workers. This may not be possible in an online crowdsourcing platform where workers are temporally and spatially separated with limited communications. In addition, workers engaged in such strategies could be detected by the platform and removed. Hence, we consider that workers report their solutions independently and restrict their solution reporting strategies to \{rd, 1, -1\} \([14], [15], [24]\).

For ease of exposition, we use \( s_i \triangleq (e_i, r_i) \) to denote worker \( i \)’s effort exertion and reporting strategy with \( s_i \in S_i \triangleq \{(0, \text{rd}), (1, 1), (1, -1)\} \).

4) Consistency Reward for Majority Voting: After workers complete the task and report their solutions, the platform compares each worker \( i \)’s reported solution \( x_{i_{\text{report}}} \) with the majority solution from the remaining workers. If they are aligned, worker \( i \) will receive a consistency reward \( R \geq 0 \).\(^4\) We use \( G_i(s; \epsilon) \) to denote the probability of worker \( i \) receiving \( R \), where \( s = ((e_i, r_i), \forall i \in \mathcal{N}) \). Note that \( G_i(s; \epsilon) \) is also a function of the platform’s information revelation strategy \( \epsilon \), which will be explained in Section III-B.

5) Worker Payoff: We define each worker \( i \)’s expected payoff as

\[
u_i(s; \epsilon, R) = G_i(s; \epsilon) \cdot R - e_i \cdot c, \tag{3} \]

where \( G_i(s; \epsilon) \cdot R \) represents the expected consistency reward and \( -e_i \cdot c \) represents the cost for effort exertion.

B. Platform’s Decisions and Payoff

In this subsection, we first define the platform’s strategies for information revelation and reward design, and then define its payoff function.

\(^1\)Many crowdsourcing applications focus on binary tasks, e.g., image labeling and online content moderation, which draw extensive attention in literature \([14], [15], [21]\). Besides, our model can be extended to the scenario where a task has more than two possible solutions, i.e., by decomposing a multi-solution task into several binary-solution tasks. For example, eliciting opinions of workers from three alternatives, i.e., good, bad or average on the quality evaluation of an online article is a three-solution task. We can decompose it into three binary-solution tasks, based on whether a worker’s evaluation is good or not, bad or not, and average or not.

\(^2\)We can extend our analysis to the scenario where even without any effort a worker still has some information about the true solution. In this scenario, the solution would always be more accurate than random guessing \([14], [21]\).

\(^3\)The rd strategy is adopted for ease of exposition. In fact, if a worker exerts no effort, his solution is equally likely to be correct or wrong. Hence, one could equivalently view that the worker is either truthfully reporting its solution or untruthfully reporting it.

\(^4\)In case a tie is incurred in the majority solution, we assume without loss of generality that, worker \( i \) still obtains the reward.
1) Platform Information Revelation Strategy: The platform has additional information regarding the workers’ solution accuracy distribution, i.e., the number of high-accuracy workers $k$. With this informational advantage, the platform can strategically announce the worker information to desired worker behavior and maximize its payoff.

The information asymmetry and revelation between the platform and the workers is modeled using a Bayesian persuasion framework [16]–[19] as follows:

- **Step 1**: neither the platform nor the workers know $k$, and the platform must commit to a long-term information revelation strategy.
- **Step 2**: the value of $k$ is realized and observed by the platform, but not the workers.
- **Step 3**: the platform announces a value $k_{\text{ann}}$ that may be different from the real value of $k$ to the workers according to its previously committed strategy.

Next, we elaborate Step 1 to Step 3 in the following:

**Step 1**: neither the platform nor workers know $k$. We consider they know the distribution of $k$, which constitutes their common prior belief $\mu_{\text{prior}} = (\mu_{\text{high}}, \mu_{\text{low}})$.

$$\mu_{\text{high}} = Pr(k = k^{\text{high}}), \quad \mu_{\text{low}} = Pr(k = k^{\text{low}}),$$
\(4\)

$\mu_{\text{high}} + \mu_{\text{low}} = 1$, and $k^{\text{high}}$ and $k^{\text{low}}$ are two possible values of $k$ satisfying $0 \leq k^{\text{low}} < k^{\text{high}} \leq N$. Note that $\mu_{\text{prior}}$ represents the workers’ prior belief before the platform announces $k_{\text{ann}}$. In practice, the workers can form such a prior belief via exploring the platform’s feedback and reputation systems [29].

It is important to note that in (4), the consideration of a two-point distribution for $k$ is just for the ease of exposition. Our analysis and results are applicable to the case when there are arbitrarily finite realizations for $k$.

Before $k$ is realized, the platform commits to an information revelation strategy. The platform may have many tasks in practice, and for each task, it may face a different worker population (i.e., different $k$). Before workers arrive (i.e., before $k$ is realized), the platform determines the information revelation strategy, and will commit to this long-term strategy, which helps it build a good reputation [18], [30]–[33].

Specifically, we use $\epsilon \triangleq (\epsilon^{h}, \epsilon^{l}) \in [0, 1]^2$ to denote the platform’s information revelation strategy. We assume that the platform announces $k_{\text{ann}} = k^{\text{high}}$ with probability $\epsilon^{h}$ when $k = k^{\text{low}}$. Moreover, we assume that the platform announces $k_{\text{ann}} = k^{\text{low}}$ with probability $\epsilon^{l}$ when $k = k^{\text{high}}$. Both $\epsilon^{h}$ and $\epsilon^{l}$ are the platform’s deception probabilities in different cases. We summarize the dependence of $k_{\text{ann}}$ on $k$ and $\epsilon$ as follows:

$$\begin{align*}
Pr(k_{\text{ann}} = k^{\text{high}} | k = k^{\text{low}}) &= \epsilon^{h}, \\
Pr(k_{\text{ann}} = k^{\text{low}} | k = k^{\text{high}}) &= 1 - \epsilon^{h}, \\
Pr(k_{\text{ann}} = k^{\text{high}} | k = k^{\text{high}}) &= 1 - \epsilon^{l}, \\
Pr(k_{\text{ann}} = k^{\text{low}} | k = k^{\text{low}}) &= \epsilon^{l}.
\end{align*}$$
\(5\)

**Step 2**: $k$ is realized according to its distribution (which is also the common prior) $\mu_{\text{prior}}$ [18], [26] and the value of $k$ is observed by the platform (e.g., via market research), but not the workers.

More specifically, once the crowdsourcing task is announced and workers have signed up the task, the platform can know the workers’ capabilities (i.e., the value of $k$) from their past performances.

**Step 3**: given $k$, the platform will announce $k_{\text{ann}}$ to the workers according to the committed strategy specified in (5). The platform will strategically choose $\epsilon$, which affects the workers’ posterior belief regarding $k$, and hence affects the platform’s reward design and payoff. Note that workers can learn the platform’s information revelation strategy via repeated interactions with the platform [34]. They can also learn such strategy via exploring the platform’s feedback and reputation systems [35].

2) Platform Reward Design Strategy: In addition to the information revelation strategy $\epsilon$, the platform also needs to decide the consistency reward per worker $R \geq 0$ to incentivize high-quality and truthful solutions. As mentioned earlier, after workers report their solutions, the platform will distribute consistency rewards to workers whose solutions match the majority. The decisions $\epsilon$ and $R$ are completely coupled, as $\epsilon$ affects the workers’ posterior belief, which together with $R$ determine the worker equilibrium outcome.

3) Platform Payoff: The platform aims to achieve a good tradeoff between the accuracy (i.e., quality) of the aggregated solution and the cost of incentivizing the workers [14], [15], [24], [36]. Specifically, we define the platform’s payoff as follows:

$$U_{\mu}(\epsilon, R, k; s) = \beta P_{\mu}(\epsilon, R, k; s) - \mathbb{E}\{R^{\text{tot}}(\epsilon, R, k; s)\},$$
\(6\)

where $P_{\mu}(\epsilon, R, k; s)$ denotes the accuracy of the aggregated solution from the workers, i.e., the probability that the aggregated solution matches the true task solution. We will use the widely adopted majority rule [13], [15] to calculate this probability. The parameter $\beta > 0$ represents the platform’s valuation of the aggregated solution’s accuracy. The term $\mathbb{E}\{R^{\text{tot}}(\epsilon, R, k; s)\}$ captures the total expected consistency rewards.

IV. SAVING THREE-STAGE MODEL

In this section, we solve the three-stage game via backward induction. Specifically, we will solve the workers’ decisions, the platform’s reward design, and the platform’s information revelation in Sections IV-A, IV-B, and IV-C, respectively.

To save space, we only consider strategic workers in this section, as the analysis is more challenging and results are
more intriguing. We will later provide numerical results for naïve workers in Section V, which serves as a benchmark.

A. Worker Equilibrium Behaviors in Stage III

Given $\epsilon$ and $R$, each worker chooses his effort exertion and solution reporting strategies $s_i$ to maximize his own payoff.

1) Worker Belief Update: Before the platform announces $k_{anu}^n$, workers have prior belief $\mu_{prior}$ regarding $k$ (see (4)). After the platform announces $k_{anu}^n$, the workers form posterior belief based on the prior belief and the announcement. Proposition 1 computes the posterior belief for strategic workers.

**Proposition 1. (Posterior Belief for Strategic Workers)** Let $\mu_{post,str}^{w,k_{anu}^n}$ denote a strategic worker’s posterior belief in $k_{anu}^n$ conditional on the platform’s announcement $k_{anu}^n$, where $w \in \{\text{high}, \text{low}\}$. Then, we have

$$
\mu_{post,str}^{\text{high}}_{k_{anu}^n}(\epsilon) = \frac{(1 - \epsilon^h) \mu_{post,str}^{\text{high}}_{prior} + \epsilon^h \mu_{post,str}^{\text{low}}_{prior}}{(1 - \epsilon^h) \mu_{post,str}^{\text{high}}_{prior} + \epsilon^h \mu_{post,str}^{\text{low}}_{prior}},
$$

(7)

$$
\mu_{post,str}^{\text{low}}_{k_{anu}^n}(\epsilon) = \frac{(1 - \epsilon^h) \mu_{post,str}^{\text{high}}_{prior} + \epsilon^h \mu_{post,str}^{\text{low}}_{prior}}{(1 - \epsilon^h) \mu_{post,str}^{\text{high}}_{prior} + \epsilon^h \mu_{post,str}^{\text{low}}_{prior}},
$$

(8)

$$
\mu_{post,str}^{\text{low}}_{k_{anu}^n}(\epsilon) = \frac{(1 - \epsilon^h) \mu_{post,str}^{\text{low}}_{prior} + \epsilon^h \mu_{post,str}^{\text{low}}_{prior}}{(1 - \epsilon^h) \mu_{post,str}^{\text{high}}_{prior} + \epsilon^h \mu_{post,str}^{\text{low}}_{prior}},
$$

(9)

$$
\mu_{post,str}^{\text{low}}_{k_{anu}^n}(\epsilon) = \frac{(1 - \epsilon^h) \mu_{post,str}^{\text{low}}_{prior} + \epsilon^h \mu_{post,str}^{\text{low}}_{prior}}{(1 - \epsilon^h) \mu_{post,str}^{\text{high}}_{prior} + \epsilon^h \mu_{post,str}^{\text{low}}_{prior}},
$$

(10)

Proof. We apply the Bayes’ rule to compute the above probabilities. We show the derivation of (7) as follows:

$$
\mu_{post,str}^{\text{high}}_{k_{anu}^n}(\epsilon) = Pr(k = k_{\text{high}}|k_{anu}^n = k_{\text{high}}) = Pr(k_{anu}^n = k_{\text{high}}|k = k_{\text{high}}) \cdot Pr(k = k_{\text{high}}) = \frac{Pr(k_{anu}^n = k_{\text{high}}|k = k_{\text{high}}) \cdot Pr(k = k_{\text{high}})}{\sum_{k \in \{k_{\text{low}}, k_{\text{high}}\}} (Pr(k_{anu}^n = k_{\text{high}}|k = k) \cdot Pr(k = k)) = \frac{(1 - \epsilon^h) \mu_{post,str}^{\text{high}}_{prior}}{(1 - \epsilon^h) \mu_{post,str}^{\text{high}}_{prior} + \epsilon^h \mu_{post,str}^{\text{low}}_{prior}}.
$$

Similarly, one can compute the probabilities in (8)-(10).

Note that $\mu_{post,str}^{\text{high}}_{k_{anu}^n}(\epsilon)$ in (7) represents the posterior belief of a strategic worker regarding $k = k_{\text{high}}$ conditional on the platform’s announcement $k_{anu}^n = k_{\text{high}}$ and it is a function of $\epsilon$ and the prior $\mu_{prior}$. One can see that $\mu_{post,str}^{\text{high}}_{k_{anu}^n}(\epsilon)$ in (7) decreases in $\epsilon^h$. This indicates that if the platform is more likely to deceive the workers via announcing $k_{anu}^n = k_{\text{high}}$ when $k = k_{\text{low}}$ (i.e., a larger $\epsilon^h$), the strategic workers hearing $k_{anu}^n = k_{\text{high}}$ will doubt the platform and are less likely to believe $k = k_{\text{high}}$ (which leads to a smaller $\mu_{post,str}^{\text{high}}_{k_{anu}^n}(\epsilon)$). Similarly, $\mu_{post,str}^{\text{low}}_{k_{anu}^n}(\epsilon)$ in (10) decreases in $\epsilon^h$. If the platform is more likely to lie announcing $k_{anu}^n = k_{\text{low}}$, the strategic workers hearing this are less likely to believe $k = k_{\text{low}}$ (i.e., a smaller $\mu_{post,str}^{\text{low}}_{k_{anu}^n}(\epsilon)$).

2) Worker Equilibrium Strategy: When the workers play the effort exertion and solution reporting game, they use their posterior belief to calculate their expected payoffs. Next, we characterize the workers’ equilibrium decisions. Similar to prior IEV literature (e.g., [14], [15], [21], [24], [25]), we focus on symmetric Nash equilibria (SNE), where workers with the same type (i.e., solution accuracy) play the same strategy.

For the ease of exposition, we first define some terminology related to the worker equilibria in Stage III.

**Definition 1. (Stage III Equilibrium Types)** (i) An $n$-SNE is defined as the profile $(s^*_i = (0, rd), \forall i \in N)$, where no worker exerts effort and truthfully reports.

(ii) An $f$-SNE is defined as the profile $(s^*_i = (1,1), \forall i \in N)$, where all the workers fully exert effort and truthfully report.

(iii) A $p$-SNE is defined as the profile $(s^*_i = (1,1), \forall i \in N_h, s^*_i = (0, rd), \forall j \in N_l)$, where high-accuracy workers exert effort and truthfully report, and low-accuracy workers exert no effort and randomly report.

Note that the workers’ equilibrium behaviors depend on the platform’s information announcement $k_{anu}^n$, which determines the workers’ posterior belief. Theorem 1 characterizes the possible equilibria among strategic workers.

**Theorem 1. (Worker Equilibria in Stage III)**

(i) Given any $\epsilon \in [0,1]^2$, an $n$-SNE exists if $R \geq 0$.

(ii) Given any $\epsilon \in [0,1]^2$, there always exists a threshold $R_{str}^f(\epsilon, k_{anu}^n) > 0$, such that an $f$-SNE exists if and only if $R \geq R_{str}^f(\epsilon, k_{anu}^n)$.

(iii) When $\epsilon \in \Phi \triangleq \{\epsilon \in [0,1]^2 \mid \text{condition (11) holds}\}$, there exist two thresholds $0 < R_{str}^f(\epsilon, k_{anu}^n) \leq R_{str}^h(\epsilon, k_{anu}^n)$, such that a $p$-SNE exists if and only if $R_{str}^h(\epsilon, k_{anu}^n) \leq R \leq R_{str}^f(\epsilon, k_{anu}^n)$, where the condition (11) is shown at the top of the next page.

Cases (i) and (ii) in Theorem 1 implies that given any $\epsilon$, an $n$-SNE and an $f$-SNE can exist under proper reward levels. In particular, they can coexist under a sufficiently large reward level (i.e., $R \geq R_{str}^f(\epsilon, k_{anu}^n)$).

Case (iii) in Theorem 1 suggests a trickier analysis of the existence of $p$-SNE. Unlike $n$-SNE and $f$-SNE, for a $p$-SNE to exist, the information revelation strategy $\epsilon$ must satisfy the condition specified in (11). In (11), $P_{\text{majority}}$ is the probability that the majority solution among $N - 1$ workers is correct when $k_{\text{high}} - 1$ high-accuracy workers use (1,1) and the remaining workers use (0, rd). Similar discussions apply for $P_{\text{majority}}^{k_{anu}^n}$, $P_{\text{majority}}^{k_{anu}^n}$, and $P_{\text{majority}}^{k_{anu}^n}$ in (11). The expressions of these probability terms are complicated, yet we can apply the Z-transform algorithm in [37] to efficiently calculate them. Condition (11) means that when exerting efforts, the high-accuracy workers believe they have a larger probability of obtaining the reward than the low-accuracy workers. If (11) is violated, the high-accuracy workers will believe the chance of obtaining the reward is small. Together with a moderate amount of reward (i.e., $R_{str}^h(\epsilon, k_{anu}^n) \leq R \leq R_{str}^f(\epsilon, k_{anu}^n)$), the expected reward for a high-accuracy worker will be small.
\[
\frac{2 \rho_h - 1}{2 \rho_l - 1} \left( \mu_{\text{post,str}} | k_p^{\text{ann}} (\epsilon) P_{\text{majority}} | k_{\text{high}} - 1 + \mu_{\text{post,str}} | k_p^{\text{ann}} (\epsilon) P_{\text{majority}} | k_{\text{low}} - 1 \right) \geq \mu_{\text{high}} | k_p^{\text{ann}} (\epsilon) P_{\text{majority}} | k_{\text{high}} + \mu_{\text{low}} | k_p^{\text{ann}} (\epsilon) P_{\text{majority}} | k_{\text{low}}. \tag{11}
\]

In this case, the high-accuracy workers will not exert effort to save the cost, and hence a p-SNE does not exist.

Next, we characterize the impact of the platform’s information revelation \( \epsilon \) on the worker equilibria in Corollary 1.

**Corollary 1.** (i) Consider a fixed \( \epsilon \). If \( k_p^{\text{ann}} = k_{\text{high}} \), \( R_f^{\text{str}} (\epsilon, k_p^{\text{ann}}) \) and \( R_{\text{pl}}^{\text{str}} (\epsilon, k_p^{\text{ann}}) \) in Theorem 1 increase in \( \epsilon \). Otherwise, if \( k_p^{\text{ann}} = k_{\text{low}} \), both values decrease in \( \epsilon \).

(ii) Consider a fixed \( \epsilon \). If \( k_p^{\text{ann}} = k_{\text{high}} \), \( R_f^{\text{str}} (\epsilon, k_p^{\text{ann}}) \) and \( R_{\text{pl}}^{\text{str}} (\epsilon, k_p^{\text{ann}}) \) in Theorem 1 also increase in \( \epsilon \). Otherwise, if \( k_p^{\text{ann}} = k_{\text{low}} \), both values decrease in \( \epsilon \).

Case (i) in Corollary 1 implies that if the platform is more likely to misreport \( k_p^{\text{ann}} = k_{\text{high}} \) (i.e., a larger \( \epsilon \)), and it indeed announces \( k_{\text{high}} \), larger rewards are needed to induce both an f-SNE and a p-SNE. The intuition is that a larger \( \epsilon \) makes the strategic workers believe that the average worker accuracy is lower (a smaller \( \mu_{\text{post,str}} | k_{\text{high}} (\epsilon) \) in (7)), and hence there is a smaller chance of matching the majority solution and obtaining the reward. As a result, the platform needs to use larger rewards to incentivize the workers. Interestingly, Case (ii) says that \( R_f^{\text{str}} (\epsilon, k_p^{\text{ann}}) \) and \( R_{\text{pl}}^{\text{str}} (\epsilon, k_p^{\text{ann}}) \) also increase in \( \epsilon \) when \( k_p^{\text{ann}} = k_{\text{high}} \). A larger \( \epsilon \) indicates that the platform is less likely to announce \( k_p^{\text{ann}} = k_{\text{high}} \) when \( k = k_{\text{high}} \). Hence, when hearing \( k_p^{\text{ann}} = k_{\text{high}} \), the strategic workers deduce that the real value is more likely to be \( k = k_{\text{low}} \). This implies a lower average worker accuracy and hence the platform needs larger rewards to incentivize them.

Note that the different SNEs in Theorem 1 can coexist under proper conditions on \( \epsilon \) and \( R \). For example, given any \( \epsilon \) and a sufficiently large \( R \), at least an n-SNE and an f-SNE coexist. When multiple SNEs are possible, we are interested in understanding whether there exists a Pareto-dominant SNE, where each worker achieves a no smaller payoff, with at least one worker achieving a strictly larger payoff, compared to that achieved in other possible SNEs [15], [17], [38]. We prove the existence of Pareto-dominant SNE in Theorem 2.

**Theorem 2. (Pareto-dominant SNE in Stage III)** Given any \( \epsilon \) and \( R \), there exists a Pareto-dominant SNE among the workers.

We assume that when multiple SNEs coexist, the workers will choose the Pareto-dominant one [15], [39], [40]. Hence, Theorem 2 enables us to solve the platform’s reward design and information revelation by focusing on the Pareto-dominant SNE among the workers.

**B. Platform Reward Design in Stage II**

In this subsection, we solve the platform’s reward design problem. Given the decided \( \epsilon \) in Stage I, the platform observes \( k \) and decides \( R \) in Stage II to maximize its payoff, anticipating the Pareto-dominant SNE in Stage III.

Before characterizing the platform’s optimal reward design, we provide several definitions for ease of exposition.

**Definition 2.** Let \( z \in \{n, f, p\} \) denote the SNE index. Define:

- \( P_z(k) \): accuracy of the aggregated solution for \( z \)-SNE.
- \( \mathbb{E} \{ R_z^{\text{tot}} (\epsilon, k, k_p^{\text{ann}}) \} \): total expected consistency reward for \( z \)-SNE.
- \( B_z (\epsilon, k, k_p^{\text{ann}}) \): Bang-per-buck for \( z \)-SNE, where

\[
B_z (\epsilon, k, k_p^{\text{ann}}) = \frac{P_z (k) - P_n (k)}{\mathbb{E} \{ R_z^{\text{tot}} (\epsilon, k, k_p^{\text{ann}}) \}}. \tag{12}
\]

One can think of \( B_z (\epsilon, k, k_p^{\text{ann}}) \) as the average accuracy improvement from \( n \)-SNE to \( z \)-SNE per unit of reward. As will be seen, the values of bang-per-buck for different SNEs will affect the platform’s optimal reward design.

Note that the terms in Definition 2 are also functions of \( k \). In Stage II, the platform observes the real value of \( k \), and will utilize it to optimize the reward design. Next, we characterize the platform’s optimal reward design in Theorem 3.

**Theorem 3. (Platform’s Reward Design in Stage II)**

(i) If (11) holds and \( B_p (\epsilon, k, k_p^{\text{ann}}) \geq B_f (\epsilon, k, k_p^{\text{ann}}) \), the platform’s optimal reward level is

\[
R^* (\epsilon, k, k_p^{\text{ann}}) = \begin{cases} 
0, & \text{if } \beta < \frac{1}{B_p (\epsilon, k, k_p^{\text{ann}})}, \\
R_f^{\text{str}} (\epsilon, k_p^{\text{ann}}), & \text{if } \frac{1}{B_p (\epsilon, k, k_p^{\text{ann}})} \leq \beta < \tilde{\beta} (\epsilon, k, k_p^{\text{ann}}), \\
R_f^{\text{str}} (\epsilon, k_p^{\text{ann}}), & \text{if } \beta \geq \tilde{\beta} (\epsilon, k, k_p^{\text{ann}}),
\end{cases}
\]

where \( \tilde{\beta} (\epsilon, k, k_p^{\text{ann}}) = \frac{\mathbb{E} \{ R_{f}^{\text{tot}} (\epsilon, k_p^{\text{ann}}) \}}{\mathbb{E} \{ R_{f}^{\text{tot}} (\epsilon, k^{\text{ann}}) \}} \).

(ii) If either (11) does not hold or \( B_p (\epsilon, k, k_p^{\text{ann}}) < B_f (\epsilon, k, k_p^{\text{ann}}) \), the platform’s optimal reward level is

\[
R^* (\epsilon, k, k_p^{\text{ann}}) = \begin{cases} 
0, & \text{if } \beta < \frac{1}{B_f (\epsilon, k, k_p^{\text{ann}})}, \\
R_f^{\text{str}} (\epsilon, k_p^{\text{ann}}), & \text{if } \beta \geq \frac{1}{B_f (\epsilon, k, k_p^{\text{ann}})}. 
\end{cases}
\]

Note that (11) is a necessary condition for a p-SNE to exist. A p-SNE exists if (11) holds and the reward level is appropriate (see Theorem 1). Hence, Theorem 3 implies that: (i) If a p-SNE exists, it has a larger bang-per-buck than an f-SNE, and the platform’s valuation \( \beta \) is moderate, the platform will elicit a p-SNE as the Pareto-dominant SNE (in Stage III) via choosing \( R^* = R_f^{\text{str}} (\epsilon, k_p^{\text{ann}}) \) to maximize its payoff. (ii) Otherwise, if either a p-SNE does not exist or it has a smaller bang-per-buck than an f-SNE, a p-SNE cannot be optimal for the platform. When \( \beta \) is large, the platform will elicit an f-SNE as the Pareto-dominant SNE via choosing \( R^* = R_f^{\text{str}} (\epsilon, k_p^{\text{ann}}) \).
In this subsection, we solve the platform’s information revelation problem. The platform decides the information revelation strategy \( \epsilon = (\epsilon^h, \epsilon^l) \in [0,1]^2 \) in Stage I to maximize its expected payoff, anticipating its own decision on \( R \) in Stage II and the workers’ Pareto-dominant SNE in Stage III. Note that the expectation is taken with respect to \( k \), as the platform needs to jointly consider different cases for \( k \) to decide \( \epsilon \).

The information revelation problem in Stage I is challenging to solve, as it is complexly coupled with the reward design in Stage II (e.g., as shown in (11)), which leads to a non-convex program. More specifically, the information revelation in Stage I affects the workers’ posterior belief, which together with the reward design in Stage II determines the workers’ equilibrium behaviors in Stage III. In addition, the workers’ decisions in Stage III are intertwined, since each worker obtains a reward if his solution matches the majority solution of the other workers. Nevertheless, we can exploit the special property of the problem to explore the solutions to Stage I.

We characterize a key property of the platform’s optimal information revelation strategy in Theorem 4.

**Theorem 4. (Platform’s Information Revelation in Stage I) It is not always optimal for the platform to set \( \epsilon^h = 1 \) and \( \epsilon^l = 0 \).**

Theorem 4 implies that the platform may not find it optimal to always announce \( k_p^{\text{ann}} = k^{\text{high}} \) (see (5)) to strategic workers. This is counter-intuitive, as one may think that the platform should stifle the workers into believing in a high overall worker capability (by always announcing \( k^{\text{high}} \)) to maximize its payoff. To understand this surprising result, we elaborate the rationale behind Theorem 4 as follows. Recall that the true value of \( k \) affects the reward design in Stage II, and the platform’s announced value \( k_p^{\text{ann}} \) affects the worker behaviors in Stage III. Therefore, to analyze the information revelation in Stage I, we consider the following four cases:

- **Case (h,h):** \( k = k^{\text{high}} \) and \( k_p^{\text{ann}} = k^{\text{high}} \), which happens with a probability \( Q_{h,h}(\epsilon) = \frac{\epsilon_{\text{prior}}}{1 - \epsilon^2} \).
- **Case (h,l):** \( k = k^{\text{high}} \) but \( k_p^{\text{ann}} = k^{\text{low}} \), which happens with a probability \( Q_{h,l}(\epsilon) = \frac{\epsilon_{\text{prior}}}{1 - \epsilon^2} \).
- **Case (l,h):** \( k = k^{\text{low}} \) but \( k_p^{\text{ann}} = k^{\text{high}} \), which happens with a probability \( Q_{l,h}(\epsilon) = \frac{\epsilon_{\text{prior}}}{1 - \epsilon^2} \).
- **Case (l,l):** \( k = k^{\text{low}} \) and \( k_p^{\text{ann}} = k^{\text{low}} \), which happens with a probability \( Q_{l,l}(\epsilon) = \frac{\epsilon_{\text{prior}}}{1 - \epsilon^2} \).

To solve \( \epsilon^* = (\epsilon^*, \epsilon^*) \) in Stage I, we first consider a fixed \( \epsilon^* \), and write the expected platform payoff as follows:

\[
\mathbb{E} \{ U_p(\epsilon^*) \} = Q_{h,h} \cdot U_{h,h}(\epsilon^*) + Q_{h,l} \cdot U_{h,l}(\epsilon^*) + Q_{l,h} \cdot U_{l,h}(\epsilon^*) + Q_{l,l} \cdot U_{l,l}(\epsilon^*),
\]

where \( U_{h,h}(\epsilon^*) \) represents the maximum platform payoff under Case (h,h) after the platform optimizes the reward in Stage II. The other notations \( U_{h,l}(\epsilon^*) \), \( U_{l,h}(\epsilon^*) \), and \( U_{l,l}(\epsilon^*) \) are similarly defined. Notice that \( U_{h,h}(\epsilon^*) \) depends on \( \epsilon^h \), as it affects the strategic workers’ posterior belief, and hence the reward design and the platform payoff.

Now, we will show that the expected platform payoff \( \mathbb{E} \{ U_p(\epsilon^*) \} \) may not be monotone in \( \epsilon^h \). To see this, we first summarize some monotonicity results in Lemma 1.

**Lemma 1.** (i) The terms \( U_{h,h}(\epsilon^h) \), \( U_{l,h}(\epsilon^h) \), and \( Q_{l,l}(\epsilon^h) \) in (15) decrease in \( \epsilon^h \). (ii) The terms \( U_{h,l}(\epsilon^h) \), \( U_{l,l}(\epsilon^h) \), and \( Q_{l,l}(\epsilon^h) \) in (15) increase in \( \epsilon^h \).

One can easily verify the monotonicity of \( Q_{l,l}(\epsilon^h) \) and \( Q_{l,h}(\epsilon^h) \) in \( \epsilon^h \) based on the definitions. We focus on the monotonicity of the platform payoff under different cases. Consider \( U_{h,h}(\epsilon^h) \) under Case (h,h), which decreases in \( \epsilon^h \), as an example. As shown in Corollary 1, under a larger \( \epsilon^h \), the platform needs to use larger rewards to incentivize the workers, which can decrease the platform payoff. Similar discussions apply for \( U_{l,h}(\epsilon^h) \), \( U_{l,l}(\epsilon^h) \), and \( U_{l,l}(\epsilon^h) \). Because different components of \( \mathbb{E} \{ U_p(\epsilon^*) \} \) in (15) have different monotonic properties, the expected platform payoff is not always monotonic in \( \epsilon^h \) (we have conducted numerical experiments to validate the non-monotonicity). One can also show that given \( \epsilon^h \), the expected payoff is not always monotonic in \( \epsilon^l \). In other words, the platform even has incentives to announce \( k^{\text{low}} \) when \( k = k^{\text{high}} \) (i.e., using a positive \( \epsilon^h \)). To conclude, the platform needs to achieve a tradeoff between being honest and lying.

The closed-form solutions of \( \epsilon^h \) and \( \epsilon^l \) are hard to derive, mainly due to the complex coupling between the reward design and the information revelation via (11), (13), (14) (see Theorem 3). Nevertheless, besides the above analysis, we will construct numerical examples in Section V to validate Theorem 4.

**V. NUMERICAL RESULTS**

In this section, we provide numerical results to investigate the impact of the workers’ characteristics and their prior belief on the overall mechanism performance.

We study two types of workers: (i) **strategic** workers who may doubt the platform’s announced information (with complete analytical results shown in Section IV); (ii) **naive** workers who put full trust in whatever the platform announces. We use notations similar to (7)-(10) (except that the superscript is changed from post, str to post, nai) to denote the naive workers’ posterior belief. Specifically, we have

\[
\begin{align*}
\mu_{\text{post,nai}}^{\text{high}} | k^{\text{high}} & = \mu_{\text{post,nai}}^{\text{low}} | k^{\text{low}} = 1, \\
\mu_{\text{post,nai}}^{\text{low}} | k^{\text{high}} & = \mu_{\text{post,nai}}^{\text{high}} | k^{\text{low}} = 0,
\end{align*}
\]

where \( \mu_{\text{post,nai}}^{\text{high}} | k^{\text{high}} \) represents a naive worker’s posterior belief in \( k = k^{\text{high}} \) conditional on the platform’s announcement \( k_p^{\text{ann}} = k^{\text{low}} \). A naive worker will discard his prior belief and fully believe in the announced value, e.g., \( \mu_{\text{post,nai}}^{\text{low}} | k^{\text{high}} = 1 \). The consideration of naive workers will serve as a benchmark comparison to strategic workers.

As will be shown, the platform always finds it optimal to announce a high average worker accuracy to naive workers, but this is not the case to strategic workers. We also show a counter-intuitive result that the platform’s payoff increases in the solution accuracy of the high-accuracy workers but may decrease in the number of these high-accuracy workers.
A. Impact of Worker Characteristics

In this subsection, we study how the optimal platform payoff, the aggregate worker payoff (defined as the summation of all the workers’ payoffs), and the social welfare (defined as the summation of the platform’s and all the workers’ payoffs) depend on the high-accuracy workers’ solution accuracy \( p_h \). In the experiments, we set \( N = 100 \), \( p_l = 0.6 \), \( \mu_{prior}^{high} = 0.7 \), \( \mu_{prior}^{low} = 0.3 \), \( k^{low} = 20 \), \( c = 1 \), \( \beta = 1000 \), choose \( k^{high} \) from the set \( \{50, 70\} \), and change \( p_h \) from 0.7 to 0.8 with a step size 0.02. Fig. 2a, Fig. 2b, Fig. 2c illustrate how the platform’s optimal payoff, the aggregate worker payoff, and the social welfare change with \( p_h \) under different \( k^{high} \), respectively.

In Fig. 2a, we observe that the platform payoff increases in \( p_h \). As the solution accuracy of the high-accuracy workers improves, the platform can generate the aggregated solution with a higher accuracy and use smaller rewards to incentivize the workers. This leads to a higher platform payoff. However, we observe that given \( p_h \) (e.g., \( p_h = 0.76 \)), the platform payoff may decrease in \( k^{high} \) (e.g., strategic workers). This is because a larger number of high-accuracy workers brings a marginally decreasing benefit to the platform, yet the total rewards may grow drastically. Note that the above observations are robust, as they hold in both the strategic and naive worker cases. One may think this conclusion resembles the one in [15], yet they are derived under significantly different game environments. Different from [15], we derive the results further accounting for both the information asymmetry and the strategic revelation between the platform and the workers. Next, we summarize the above observations as follows:

**Observation 1.** The platform’s optimal payoff increases in the high-accuracy workers’ solution accuracy \( p_h \), but it may decrease in the number of the high-accuracy workers \( k^{high} \).

In Fig. 2a, we also observe that given \( p_h \) and \( k^{high} \) (e.g., \( p_h = 0.76, k^{high} = 50 \)), the platform payoff in the naive worker case is always larger than that in the strategic worker case. The platform can better manipulate the naive workers’ belief, which helps achieve a higher platform payoff. We summarize the observation as follows:

**Observation 2.** The platform benefits from workers’ naiveness.

In Fig. 2b, it is interesting to observe that the aggregate worker payoff may decrease in \( p_h \) (e.g., \( p_h \geq 0.74 \) for strategic workers). This is because the platform can harvest larger benefits from more capable (accurate) workers, leading to smaller worker payoffs. This result also bears important strategic implications. Consider the scenario where a platform aims to estimate workers’ accuracy by asking them to report this information [21]. Workers may not reveal a high accuracy (even if it is the truth), as doing so may benefit the platform but hurt the workers. We summarize the observation as follows:

**Observation 3.** More capable workers may suffer: a worker population with an overall higher accuracy may unexpectedly obtain a smaller aggregate payoff.

In Fig. 2c, we observe that the social welfare increases in \( p_h \). Note that the reward terms are canceled in the social welfare, and a larger \( p_h \) enables the platform to generate an aggregated solution with higher accuracy. As a result, the social welfare improves. We summarize the observation as follows:

**Observation 4.** The social welfare increases in the high-accuracy workers’ solution accuracy \( p_h \).

B. Impact of Worker Prior Belief

In this subsection, we study the impact of the workers’ prior belief on the optimal platform payoff, the aggregate worker payoff, and the corresponding information revelation strategies. In the experiments, we set \( N = 100 \), \( p_l = 0.6 \), \( p_h = 0.75 \), \( k^{low} = 20 \), \( c = 1 \), \( \beta = 1000 \), and consider \( \mu_{prior}^{high} \in \{0.01, 0.2, 0.4, 0.6, 0.8, 0.99\} \).

1) Impact of Worker Prior Belief on Platform/Worker Payoff: We first study how the optimal platform payoff and the aggregate worker payoff are affected by the workers’ prior belief, as shown in Fig. 3a and Fig. 3b, respectively.

2) Impact of Worker Prior Belief on Aggregated Solution: We analyze the effect of the workers’ prior belief on the aggregated solution accuracy.

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7 We apply the exhaustive search algorithm to find the optimal information revelation strategies. This is reasonable as they are long term strategies and hence are fixed within a long period.

8 We do not assign 0 or 1 to \( \mu_{prior}^{high} \) because under either assignment, the problem degenerates to the case where the platform’s information revelation strategy imposes no effect on the strategic workers’ posterior belief. For example, if \( \mu_{prior}^{high} \neq 0 \), any \( \epsilon^h \) and \( \epsilon^l \) will result in the same posterior belief \( \mu_{prior \Rightarrow high}^{high} = 0 \) (see (7)).
In Fig. 3a, we observe that given \( k_{\text{high}} \), the platform’s optimal payoff increases in \( \mu_{\text{prior}} \). The reasons are two-fold. First, the real value of \( k \) is drawn according to \( \mu_{\text{prior}} = \left( k_{\text{high}}, \mu_{\text{prior}} \right) \). A larger \( \mu_{\text{prior}} \) implies that the number of high-accuracy workers is more likely to be \( k_{\text{high}} \) than \( k_{\text{low}} \). Hence, the platform is more likely to generate an aggregated solution with a higher accuracy. This holds for both the strategic and naive workers. Second, (i) for strategic workers, the more they are inclined to believe \( k = k_{\text{high}} \) a priori, the more they also believe \( k = k_{\text{high}} \) following the information announcement. Hence, the platform can use smaller rewards to incentivize them, and hence achieves a higher payoff. (ii) For naive workers, they will trust whatever information is announced and discard the prior. Hence, the rewards needed do not depend on \( \mu_{\text{prior}} \). The platform’s optimal payoff also increases due to a more accurate aggregated solution.

In Fig. 3b, we observe that the strategic workers’ aggregate payoff decreases in \( \mu_{\text{prior}} \). This is because the platform will use smaller rewards to incentivize them, which leads to a smaller aggregate worker payoff. Interestingly, the naive workers’ aggregate payoff does not change in \( \mu_{\text{prior}} \), since the rewards do not depend on \( \mu_{\text{prior}} \), as discussed above. Based on Fig. 3a and Fig. 3b, we summarize the observations as follows:

**Observation 5.** (i) The platform’s optimal payoff increases in the workers’ prior belief \( \mu_{\text{prior}} \).
(ii) The strategic workers’ aggregate payoff decreases in \( \mu_{\text{prior}} \), while that of naive workers is independent of \( \mu_{\text{prior}} \).

2) **Impact of Worker Prior Belief on Platform Information Revelation:** Fig. 3c illustrates how the platform’s information strategies change with \( \mu_{\text{prior}} \) (consider \( k_{\text{high}} = 70 \)). We observe that \( \epsilon^* = 1 \) and \( \epsilon^* = 0 \) for naive workers. The platform should always announce a high average worker accuracy to naive workers, as it will require the minimum rewards to incentivize them.\(^5\) However, this may not be true for strategic workers where the platform chooses \( \epsilon^* \) smaller than 1 (e.g., \( \mu_{\text{prior}} = 0.4 \) for the red curve). Interestingly, the platform even has incentives to announce a lower average solution accuracy than its actual value by choosing a positive \( \epsilon^* \) (e.g., \( \mu_{\text{prior}} = 0.6 \) for the blue curve). These observations validate Theorem 4, and are summarized as follows:

**Observation 6.** The platform always finds it optimal to announce \( k_{\text{high}} \) to naive workers, but not to strategic workers. It may even announce \( k_{\text{low}} \) to strategic workers when \( k = k_{\text{high}} \).

In Fig. 3c, when the strategic workers are more confident in \( k = k_{\text{high}} \) a priori (i.e., a larger \( \mu_{\text{prior}} \)), the platform should announce \( k_{\text{ann}} = k_{\text{high}} \) less frequently (i.e., a smaller \( \epsilon^* \) and a larger \( \epsilon^* \)). As a result, the strategic workers will be more inclined to believe \( k = k_{\text{high}} \). This benefits the platform since the required rewards to incentivize the workers can be reduced. We summarize the observations as follows:

**Observation 7.** For strategic workers, the platform’s optimal information revelation strategy \( \epsilon^* \) decreases in the workers’ prior belief \( \mu_{\text{prior}} \), while \( \epsilon^* \) increases in \( \mu_{\text{prior}} \).

VI. Conclusion

In this paper, we study strategic information revelation in an IEWV problem. The problem is a challenging non-convex program, yet we exploit its special structure to characterize the properties of the optimal solutions. We show that for naive workers, the platform should always announce a high average worker accuracy. However, for strategic workers, it needs to tackle a tradeoff and may even have an incentive to announce an average accuracy lower than the actual value. Moreover, we show the surprising result that the platform payoff may decrease in the number of high-accuracy workers.

For the future work, we plan to study the problem under multi-dimensional worker heterogeneity, where both the workers’ costs and solution accuracy are heterogeneous. Moreover, it will be interesting to study costly information revelation (with cost incurred by information acquisition) in future work.

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