An Integrated Incentive Framework for Mobile Crowdsourced Sensing

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An Integrated Incentive Framework for Mobile Crowdsourced Sensing

Wei Dai, Yufeng Wang*, Qun Jin, and Jianhua Ma

Abstract: Currently, mobile devices (e.g., smartphones) are equipped with multiple wireless interfaces and rich built-in functional sensors that possess powerful computation and communication capabilities, and enable numerous Mobile Crowdsourced Sensing (MCS) applications. Generally, an MCS system is composed of three components: a publisher of sensing tasks, crowd participants who complete the crowdsourced tasks for some kinds of rewards, and the crowdsourcing platform that facilitates the interaction between publishers and crowd participants. Incentives are a fundamental issue in MCS. This paper proposes an integrated incentive framework for MCS, which appropriately utilizes three widely used incentive methods: reverse auction, gamification, and reputation updating. Firstly, a reverse-auction-based two-round participant selection mechanism is proposed to incentivize crowds to actively participate and provide high-quality sensing data. Secondly, in order to avoid untruthful publisher feedback about sensing-data quality, a gamification-based verification mechanism is designed to evaluate the truthfulness of the publisher’s feedback. Finally, the platform updates the reputation of both participants and publishers based on their corresponding behaviors. This integrated incentive mechanism can motivate participants to provide high-quality sensed contents, stimulate publishers to give truthful feedback, and make the platform profitable.

Key words: mobile crowdsourced sensing; incentive mechanism; reverse auction; gamification; reputation updating

1 Introduction

Crowdsourcing has emerged as an effective way to perform tasks that are easy for humans but remain difficult for computers. Nowadays, smart phones are ubiquitous and widely used around the world. Rich

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sensors (e.g., GPS, accelerometer, camera, etc.) are built into these devices, and they have multiple radios (e.g., WiFi, cellular, etc.). These enable individuals to sense, collect, process, and distribute people-related data at any time and place. Naturally, the mixing of smartphone-based mobile technologies and crowdsourcing offers vaster resources of computation than previously available, and leads to a new paradigm called Mobile Crowdsourcing Sensing (MCS)[1].

There exist numerous MCS applications in various fields, ranging from sharing prices of customer goods[2], to monitoring various aspects of the urban environment, such as air pollution. For example, in order to deal with the issues engendered by urbanization’s rapid progress, such as traffic congestion, energy consumption, and pollution, it has been proposed to tackle these issues by using data collected by crowds[3]. Regardless of the characterization given by various MCS applications,
three common components are present: the publishers who have sensing tasks to be outsourced to the mobile participants; the mobile participants who complete sensing tasks and offer sensed content to publishers; and the platform (usually cloud-based) that facilitates the interactions between mobile participants and publishers, including publishing tasks, selecting working participants (e.g., through reverse auction), monitoring participant task enforcement, and auditing publisher feedback.

Incentive mechanisms play an important role to guarantee a stable scale of participants, and to improve the accuracy/coverage/timeliness of the sensing results. Along this line, a considerable amount of research has been conducted recently, ranging from experimental studies to theoretical solutions and practical applications, aiming at providing more comprehensive incentive procedures and protecting the interests of different system stakeholders.

Many up-to-date surveys have summarized the taxonomy and applications of incentive mechanisms in MCS systems. In Ref. [4], the incentive taxonomy is divided into two parts, based on the purpose of the existing mechanisms: application-specific and general-purpose incentive mechanisms. Furthermore, incentive strategies research can also be divided into two categories: user-centric and platform-centric methods [5]. User-centric approaches focus on how to recruit more users and improve their motivation. Reference [6] proposed a mechanism named “Top-k rule” in a reverse auction, to have individuals participate in a pre-qualification stage. Bidders with top-k qualities were selected for the contest. The selected participants paid an entry fee for participation, then used their data for bidding; the platform selected the winner and rewarded him/her. Platform-centric approaches focus on how to improve the information gain of the platform and reduce overall sensing costs. For example, Luo et al. [7] aimed at maximizing the received contribution and profit for the platform. They argued that since all participants contributed their data, all of them should be paid some monetary reward as an incentive to offset their sensing cost, and keep them contributing to future tasks. This is termed an “all-pay auction” scheme.

However, these works have some weak points: First, they only investigated the utility of partial roles in MCS, i.e., the utility to participants and the platforms’ profit. The behavior of the third component, the publisher, is not examined at all, especially when publishers must evaluate data quality. Second, they only deal with individuals’ incentives to participate, ignoring how to incentivize publishers to provide truthful feedback. Third, as described in Ref. [5], task publishers and platforms should be treated separately, since in practice they are two different independent economic entities. The same task publisher may send tasks to different platforms in a nearby area, and similarly these platforms can recruit help from different groups of participants based on different sets of collected sensory data. Most existing research combines platforms with publishers.

To address the above issues, this paper proposes a novel incentive framework for MCS, which smoothly integrates three widely popular incentive methods: reverse auction, gamification, and reputation updating. The proposed incentive mechanism can motivate participants to provide high-quality sensory data reports, stimulate publishers to give truthful feedback about the quality of collected data, and make platforms profitable.

This paper is organized as follows. Related work is discussed in Section 2. Section 3 provides the details of our proposed incentive framework, including reverse-auction-based two-round participant selection, gamification-based verification, and reputation updating for participants and publishers. Theoretical analysis of the proposed mechanism is offered in Section 4. Finally, we briefly conclude this paper.

2 Related Work
Incentive rewards used in various applications are different. Some are designed to directly pay participants money as a reward, while others aim to reward them psychologically. In Ref. [8], the incentive rewards are divided into three categories: entertainment, services, and money. In this paper, we simply classify available incentive rewards into two categories: monetary and non-monetary, as shown in Fig. 1.

2.1 Monetary rewards
Paying for sensed data in crowd sensing tasks is the most intuitive incentive, as it turns sensed data into

![Incentive rewards](image)

**Fig. 1** Different kinds of incentives in existing applications.
goods in a free market. Any user who would like to make some money can sell her sensed data for crowd sensing tasks.

Amazon Mechanical Turk is a famous platform that serves as a programmatic interface for tasks that are easier for humans than for machines, and most people consider it a labor market[9]. Medusa is a platform that provides abstractions for specifying the steps required to complete a crowd sensing task[10]. Both platforms use monetary rewards to implement their incentive schemes, where fees are paid for each task in order to compensate contributors who complete the task. In the literature, auction-based mechanisms are mostly used to reduce the sensing cost of the publishers and improve the quality of sensing results. However, once money is involved, designing an efficient price negotiation procedure, and ensuring payment become the major issues.

2.2 Non-monetary rewards

Non-monetary rewards consist of credit, intrinsic incentives, and ranking. For instance, TruCentive focuses on encouraging participants to contribute high-quality Parking Availability (PA) information, and preventing malicious participants from spamming the parking service with high volumes of useless data[11]. TruCentive uses system credits as incentives. Intrinsic incentive factors can include mental satisfaction gained from performing the crowdsourced activities, self-esteem, personal skill development, and knowledge sharing through crowdsourcing (e.g., Wikipedia)[12]. Reputation is a special kind of ranking incentive. Reputation score, based on both the quality of contributions and the trust of participants, is calculated for each participant as a result of the trust ratings assigned to him[13]. The main purpose of using non-monetary rewards is to obtain accurate sensory data and avoid malicious participants. In comparison with monetary rewards that reflect the transient quality of the sensing data, non-monetary rewards, especially reputation, are rather long-term accumulated metrics for both participants and publishers.

Our paper takes both monetary and non-monetary rewards into consideration in designing an integrated incentive framework for MCS. Our previous work proposed an incentive mechanism, QuaCentive, that simultaneously exploited monetary (i.e., reserve auction) and non-monetary rewards (i.e., gamification and reputation)[12]. However, it only offered a simple participation selection method, and did not give clear procedures for implementing gamification and reputation updating. This paper significantly extends our previous work in the following ways: designing a reverse-auction-based two-round participant selection mechanism that can effectively exclude malicious participants, providing detailed procedures for reputation updating for participants and publishers, and offering a theoretical analysis of the properties of our proposal.

3 Proposed Incentive Framework

As described in Ref. [1], generally, three stakeholders are involved in an MCS system: crowd participants, task publishers (i.e., crowdsourcer), and a crowdsourcing platform. Our proposed incentive mechanism framework, as shown in Fig. 2, pertaining...
to all three players, is composed of three components: a reverse-auction-based two-round participant selection process, gamification-based verification, and reputation updating for participants and publishers. These three components are described below.

- The reverse-auction component completes task assignment and deposit of payments, selection and recruitment of participants, calculation of trustworthiness of data, and publisher feedback about the quality of sensing data.
- In gamification, after participants upload data and publishers evaluate the quality of the data, if the quality is bad, then the platform utilizes gamification to recruit individuals that enjoy the verification game to simply vote whether the publisher’s rating is truthful, and then infers appropriate evaluations of the data quality.
- The reputation updating component updates participants’ and publisher’s reputation scores according to the trustworthiness of the data, the publisher’s feedback, and her credibility.

Now we describe the detailed operations of the integrated incentive mechanism. For clarity, Table 1 lists the notations and their meanings, as used in this paper.

### 3.1 Reverse auction

#### 3.1.1 Task assignment and deposit payment

A publisher “buys” a sensing service from the crowdsourcing platform, through paying a deposit to the platform. The amount of money paid by publishers depends on the bid price of participants, platform profits, and extra gamification expense. Note that the deposit from the publisher will be refunded if and only if the publisher reports that the service failed (bad rating on sensed data), and the failure report is successfully verified by the platform through gamification. Therefore, the deposit payment itself is only for the purpose of vouching.

A publisher provides a short description of the task, describing its nature, time limitations, and so on. Note that tasks should be divided into small pieces that can be easy for mobile devices. Then, the platform distributes task details to the crowd to recruit participants through an open call.

#### 3.1.2 Two-round selection and recruitment of participants

In the first round, the platform selects participating candidates according to the intuitive requirements of the publisher, such as limitations of profession, age, sex, etc. Note that, to understand the impact of financial incentives on paid participants’ willingness to behave maliciously, Ref. [14] conducted a series of experiments, in which the authors hired crowd workers via one crowdsourcing task (Attack task) to attack a different crowdsourcing task (Target task). They found that one-third of all workers were unwilling to attack the Target task, despite high Attack task payments. Thus, it may be possible to identify a subset of these as ethical workers for tasks that require good behavior. To fulfill the above goal of filtering potential malicious participants, the platform can use an Ethical Gold test to identify a subset of the ethical participants—for example, they might ask participants to attack another task, and then only move forward with participants who refuse to do this job. Only participants who have passed the first selection have the right to bid price on the task.

On second-round selection, the platform chooses participants according to the ascending order of each individual i’s ranking price $S_i$, defined by Eq. (1), depending on the participant’s bid price $b_i$ and reputation $RE_{pa}^i$.

$$S_i = b_i \times (1 - RE_{pa}^i)$$  

(1)

Intuitively, under a constant bid price, if the value of $RE_{pa}^i$ is higher, $S_i$ will be lower, and the probability that participant $i$ will be selected increases. This explains the effect of reputation.

Finally, the platform chooses $m$ participants
according to $S_i$, where $m$ satisfies $\sum_{i=1}^{m} b_i < P_{pu}$. In this step, the ranking price is only used in ranking for selection; what participant $i$ finally gets is still the bid price.

3.1.3 Initial inference of trustworthiness of data provided by each participant

Once the sensing data from the chosen participants is received, the platform has to calculate the trustworthiness of data provided by participant $i$ ($T_{od_i}$) before it is sent to the publisher. As in Ref. [13], the quality of data, $Q_i$, and the trustworthiness level of participant, $T_i$, are combined to obtain a final trustworthiness rating for the data. There has been much research into data quality calculation, including outlier detection and other issues[15]. Our system relies on these state-of-the-art methods for determining $Q_i$. Note that $Q_i$ is in the range of $[0, 1]$. $T_i$ is defined in Eq. (2):

$$T_i = \frac{n(\text{TE} \cap \text{PE})}{n(\text{TE})} \quad (2)$$

The set TE contains the Task’s required Expertise, and PE is the set of a Participant’s Expertise; $n(A)$ is the number of elements in set $A$.

The term $T_{od_i}$ is defined in Eq. (3):

$$T_{od_i} = \alpha \cdot Q_i + (1 - \alpha) \cdot T_i \quad (3)$$

where $\alpha$ is a constant that regulates the relative importance of $Q_i$ and $T_i$. For example, $\alpha$ can be set to 0.7 if the platform thinks quality is more important. Obviously, $T_{od_i}$ is in the range of $[0, 1]$.

3.1.4 Publisher’s feedback on data quality

Publisher gives an evaluation $e_{pu}$ of the data. The criterion for judging $e_{pu}$ is shown below.

$$e_{pu} \in \begin{cases} 
0.6, 1.0, & \text{good rating;} \\
0.0, 0.6, & \text{bad rating.}
\end{cases}$$

If the publisher’s feedback is a good rating, then the transaction is successfully completed, and the platform pays participant $i$’s bid price as a reward. Otherwise, the platform carries out gamification to verify whether the publisher’s evaluation is truthful or not.

3.2 Gamification-based verification

If the publisher’s feedback about data quality is to give it a bad rating, there may exist two distinct cases. The first is that the publisher’s evaluation is ground-truth—that is, the data quality of participant $i$ is actually bad. The second is that the publisher might want to use the sensing reports provided by participants, but pay participants as little as possible—probably through false-reporting the quality of sensing reports. To solve this issue, this framework explicitly utilizes gamification-based verification to infer whether a publisher’s feedback is truthful. Gamification is defined as the use of game design elements in non-game contexts[16]. Specifically, the platform recruits $n$ gamers and gives each gamer a small reward, $c$. Then the gamers offer an evaluation $e_g$ of the data quality through voting. The comparison algorithm in pseudocode is given below, to obtain a final evaluation of data quality, $e$, through balancing the influences of the two ratings.

Note that the small reward $c$ paid to each game is optional for the platform. The reason for setting a small reward lies in the following consideration. The gamification used in our proposed framework could be seen as one special interesting crowdsourced task, in which the platform acts in the role of “publisher”, while gamers play the role of “participants”. Furthermore, it is observed that workers primarily seek fun in gamification, but readily accept the financial incentive as an additional stimulus[17]. Therefore, initially, this setting can attract workers to complete a verification task at a comparatively low pay rate, and then once workers enjoy the game process, they will continue playing with no expectation of financial compensation.

The basis for the comparison algorithm, as shown in Algorithm 1, is explained as follows.

If $e_g \in [0, 0.6]$, that implies both ratings (publisher’s feedback and gamer verifications) are bad; in this case, the publisher’s feedback is regarded as truthful. In this case, the final rating is further computed as: When $\Delta \geq 0.3$, we take $e = (e_g + e_{pu})/2$ to smooth the relatively large quantitative gap between the two ratings; otherwise, let $e = e_{pu}$ (implying that the gap between two ratings is small enough to accommodate this supposition).

If $e_g \in (0.6, 1]$ and $\Delta \geq 0.4$, that implies that gamers gave a good rating, the publisher gave a bad rating, and the gap between those ratings is large enough for the gamers’ evaluation to be regarded as correct (i.e., the publisher provided untruthful feedback). We then let $e = e_g$; otherwise, if $\Delta \in [0.2, 0.4)$, that means the gap between those two ratings is moderate; we then take $e = (e_g + e_{pu})/2$, and compare it with the threshold between the good and bad rating, 0.6, to infer whether the publisher’s feedback is truthful or not. When $\Delta \in [0, 0.2)$, we simply take $e = e_{pu}$. It means that the gap is so small that we can trust the
Algorithm 1: Comparison algorithm framework

Input:
\( e_{pu}; \) /* publisher’s evaluation on data */
\( e_{g}; \) /* gamers’ evaluation on data */

Output:
\( e; \) /* actual evaluation that will be used in participant’s reputation updating */
rating; /* whether publisher’s feedback is truthful */

1: LET \( \Delta = e_{g} - e_{pu}; \)
2: IF \( e_{g} \leq 0.6 \)
3: IF \( \Delta \geq 0.3 \)
4: \( e = (e_{g} + e_{pu})/2; \) rating=truthful;
5: ELSE
6: \( e = e_{pu}; \) rating=truthful;
7: ELSE
8: IF \( \Delta \geq 0.4 \)
9: \( e = e_{g}; \) rating=untruthful;
10: IF \( \Delta \geq 0.2 \) AND \( \Delta < 0.4 \)
11: \( e = (e_{g} + e_{pu})/2; \)
12: IF \( e \leq 0.6 \)
13: rating=truthful;
14: ELSE
15: rating=untruthful;
16: ELSE
17: \( e = e_{pu}; \) rating=truthful;
18: END IF

Publisher’s feedback.

Through this comparison algorithm, the platform can infer whether the publisher’s feedback is truthful or not. If the publisher’s rating is truthful, the publisher will have a refund of \((b_{1} + n \cdot c)\), which means the publisher does not have to pay the extra expense of gamification; otherwise, a refund is not given, and the publisher’s actual payment will be \((b_{2} + b_{1} \cdot p + 2 \cdot n \cdot c)\), in which the first term \(b_{1}\) is the reward to participant \(i\), the second term \(b_{1} \cdot p\) is the profit of the platform, one \(n \cdot c\) is the expense of gamification, and another \(n \cdot c\) is the penalty imposed on the publisher for providing false feedback.

In summary, after gamification, we can get the value of \(e\) (correct evaluation of data quality) and know whether the publisher is truthful or not.

3.3 Reputation updating

After transactions, as shown in Fig. 3, the platform will update both the participants’ and the publisher’s reputation.

Updating Participant \(i\)’s reputation \(RE_{pa}^{i}\): This depends on the trustworthiness of data, Tod, and the effect of the final rating on data quality, \(E\). The term Tod comes from the reverse auction phase. \(E\) characterizes how the final rating of data quality affects participant \(i\)’s reputation, which is given in Eq. (4). Specifically, participant \(i\)’s reputation, \(RE_{pa}^{i}\), is updated as shown in Eq. (5).

\[
RE_{pa}^{i} = \frac{RE_{pa}^{i} + (Tod_{i} - \text{thre}Tod) \cdot k_{1} + E \cdot k_{2}}{1 + (Tod_{i} - \text{thre}Tod) \cdot k_{1} + E \cdot k_{2}}
\]  

(5)

The term threTod is the predefined threshold value determined by the platform. If the value Tod$_{i}$ is greater than threTod, that implies that the trustworthiness of participant \(i\)’s data is high, which will have a positive effect on participant \(i\)’s reputation. \(k_{1}\) and \(k_{2}\) are constants defined by the platform to adjust the speed of reputation updating and are less than 1.

**Updating the publisher’s reputation \(RE_{pu}\):** This mainly depends on the publisher’s creditability, \(x\), which, in turn, is decided by whether the publisher’s feedback is truthful. In our paper, creditability \(x\) is defined by Eq. (6).

\[
x = \frac{n(\text{truthful rating}) \cdot n(\text{untruthful rating})}{n(\text{total rating})}
\]  

(6)

where \(n(\text{truthful rating})\) denotes the number of truthful ratings made by the publisher, including the number of good ratings and the number of bad ratings that are verified by the platform as truthful; \(n(\text{untruthful rating})\) is the number of false ratings, as judged by the platform through gamification; \(n(\text{total rating})\) is the total number of feedback values provided by the
publisher. Obviously, the value of \( x \) ranges from \(-1\) to 1.

The platform calculates the publisher’s current reputation, \( cRE_{pu} \), using a Gomperz function\(^\text{[18]}\), shown as Eq. (7).

\[
cRE_{pu} = e^{\beta \cdot e^{\gamma \cdot x}} \quad (7)
\]

where \( \beta \) and \( \gamma \) are function parameters.

Finally, we update the publisher’s reputation by means of a sliding window average, as in Eq. (8).

\[
RE_{pu} = \alpha \cdot RE_{pu} + (1 - \alpha) \cdot cRE_{pu} \quad (8)
\]

where \( \alpha \) is a constant defined by the platform.

The reputation score plays an important role in the whole mechanism; thus, both stakeholders (participants and publishers) will try to behave honestly, to get a high reputation ranking.

### 4 Theoretical Analysis

In this section, we analyze the properties of integrated incentive framework from the viewpoints of three stakeholders in MCS: participant, publisher, and platform.

Table 2 gives the payoff matrix between the platform and a publisher. Note that rows indicate the publisher’s feedback on sensing data quality. The columns show whether the publisher’s feedback is truthful or not, arbitrated by gamification-based verification. For each of the 2-tuples, the first element is the publisher payment and the second is the platform profit. Successful transactions are marked with a \( \sqrt{\text{✓}} \). The utility of participant \( i \) is simply related to whether the sensing data transaction is successful or not: if successful, utility \( u_i = b_i - c_i \); otherwise, \( u_i = -c_i \).

#### 4.1 From participants’ viewpoints: Individual rationality and influence of reputation updating

**Individual rationality:** Assuming gamification-based verification can accurately detect publishers’ false reporting with probability approaching 1, then each participant \( i \) who provides high-quality data will have a non-negative utility: \( u_i \geq 0 \).

When a transaction is successful (there are two successful transactions, marked with a \( \sqrt{\text{✓}} \) in Table 2), then participant \( i \) will get bid price \( b_i \) that is larger than its cost \( c_i \). However, if the transaction fails, which means participant \( i \) sends low-quality data, he may not only receive a bad rating from the publisher, which will decrease his reputation, but also get no bid price from the publisher, that is, he has to bear the loss on his own (the utility becomes \( -c_i < 0 \)). Therefore, when the gamification-based verification can accurately judge a publisher’s reporting as false, with the probability limited to 1, the optimal strategy of each participant is to provide high-quality data.

**Reputation influence:** Reputation plays an important role in ranking price and prevents malicious attacks. Note that the second-round selection in a reverse auction uses ranking price \( S_i = b_i \times (1 - RE_{pu}) \) to select participants. Obviously, if the reputation score is higher, then the possibility of being selected is higher, which will, in return, result in positive revenue for selected participants.

Reputation can be a good way to avoid malicious attacks. For example, a malicious participant with low reputation has to bid lower (probably lower than his cost) to be chosen. Even if low bidding could make him be selected, he still cannot get his bid price, due to the fact that the publisher has a truthful bad rating on his bad-quality data. Meanwhile, he would face a loss of compensation for his sensing, and a decrease of reputation. Figure 4 graphically illustrates the change trend of a participant’s reputation updating characterized by Eq. (5). For clarity, we let \( a = (Tod_i - threTod) \cdot k_1 + E \cdot k_2 \) in Eq. (5).

In Fig. 4, we observe that the curves are qualitatively concave, that is, the absolute reputation score monotonically increases, but the incremental speed becomes less and less, which represents a diminishing marginal return. This trend perfectly fits the reputation updating rule in real social life: We can have a quick increase at the beginning, while the incremental speed slows down when the reputation

| Table 2 Payoff matrix between platform and publisher. |
|-----------------------------------------------|
| **Platform** | **Publisher** | **Good rating (without gamification)** | **Bad rating (gamification required)** |
| Game-based verification | Truthful | \( \left( \frac{b_i \cdot (1 + p)}{b_i \cdot p} \right) \sqrt{\text{✓}} \) | \( \left( \frac{b_i \cdot p}{b_i \cdot p - n \cdot c} \right) \sqrt{\text{✓}} \) |
| | Untruthful | \( \left( \frac{b_i \cdot (1 + p)}{b_i \cdot p} \right) \sqrt{\text{✓}} \) | \( \left( \frac{b_i \cdot (1 + p) + 2 \cdot n \cdot c}{b_i \cdot p + n \cdot c} \right) \sqrt{\text{✓}} \) |
Fig. 4 Illustration of the updating trend of a participant’s reputation.

Figure 5 graphically illustrates the shape of publisher’s reputation updating characterized by Eq. (7), with the change of publisher’s creditability. Obviously, it has an ‘S’ shape (sigmoid curve), which is caused by the intrinsic property of the Gomperz function used in Eq. (7). That is, initially, the curve is convex (i.e., incremental speed increases), and when passing a specific tipping point, the curve becomes concave (i.e., diminishing marginal return). The underlying rationale for the special shape lies in that, in our incentive framework, the value of the publisher’s creditability ranges from -1 to 1; therefore, this ‘S’ curve can make the publisher quickly jump out of the trap of negative creditability, and, while it is not easy, build and maintain a very positive reputation with the increase in its creditability.

4.2 From a publisher’s viewpoint: Budget feasibility, truthful feedback about quality of sensed data, influence of reputation

Budget feasibility and truthful feedback about quality of sensed data: The incentive mechanism needs to be budget feasibility for a publisher: actual\(P_{\text{pu}}\) ≤ advance\(P_{\text{pu}}\). That is, the actual payment actual\(P_{\text{pu}}\) should not be larger than the deposit amount advance\(P_{\text{pu}}\) (advanced payment). Moreover, truthful feedback about data quality is the publisher’s best strategy.

The proposed mechanism can satisfy properties of the budget feasibility and truthful feedback.

The publisher’s expected payment \(P_{\text{pu}}\) is defined by Eq. (9):

\[
P_{\text{pu}} = \sum_{i=1}^{m} b_i + P_{\text{plat}} + G \tag{9}
\]

where \(b_i\) represents the bid price of participant \(i\), \(P_{\text{plat}}\) represents platform profits, and \(G\) represents the expense of gamification.

\(P_{\text{plat}}\) is defined in Eq. (10):

\[
P_{\text{plat}} = \sum_{i=1}^{m} b_i \cdot p, \tag{10}
\]

where \(k\) is a constant, representing the regular commission fee charged by the platform; \(\text{threRE}_{\text{pu}}\) is the threshold value set by the platform. Equation (10) denotes that if the reputation of publisher is higher than the threshold \(\text{threRE}_{\text{pu}}\), the platform will charge the publisher a commission fee with a discount: the higher the reputation, the larger the discount.

Assume in a task that the number of good ratings is \(m_1\), the number of bad but truthful ratings is \(m_2\), the number of untruthful bad ratings is \(m_3\), and \(m = m_1 + m_2 + m_3\) represents the number of total ratings in this task. Then the publisher’s creditability is given as \(x = \frac{m_1}{m_1 + m_2 - m_3}\).

In our framework, the publisher first pays a deposit advance\(P_{\text{pu}}\) to the platform; then the platform selects \(m\) participants under the budget constraint of advance\(P_{\text{pu}}\). We then have the following inequality:

\[
\text{advance}P_{\text{pu}} \geq \sum_{i=1}^{m} b_i + P_{\text{plat}} + G = \sum_{i=1}^{m} b_i \cdot (1 + p) + G \tag{11}
\]
Let $x_0$ be the publisher’s creditability in the former task. It is reasonable to assume that the platform can estimate the gamification expense $G$ in the current task based on that of the former task. We have $G = (1 - x_0) \cdot m \cdot n \cdot c$. Therefore, the platform can select $m$ participants, such that Inequality (11) is satisfied.

To calculate the actual profit, we can use Eq. (12): 
\[
\text{actual}_{pu} = m_1 b_1 (1 + p) + m_2 b_1 \cdot p + 
\sum_{i=1}^{m_1} b_i \cdot (1 + p) + m_3 \cdot 2 \cdot n \cdot c = 
\sum_{i=1}^{m_1} b_i + \sum_{i=1}^{m_3} b_i \cdot p + (1 - x) \cdot m \cdot n \cdot c
\]

Then, applying Inequality (11) and Eq. (12), we obtain 
\[
\text{advance}_{pu} - \text{actual}_{pu} \geq \sum_{i=1}^{m_2} b_i + (x - x_0) \cdot m \cdot n \cdot c
\]

Therefore, if the publisher’s current creditability is not smaller than his former value, the value of $(x - x_0)$ is positive, and his actual payment will always be smaller than his advance payment (i.e., deposit money). Moreover, in order to pay less money under a budget constraint, the best strategy for the publisher is to provide truthful feedback.

**Reputation influence:** In Eq. (10), when the publisher’s reputation is higher than the threshold determined by the platform, the platform will charge the publisher a discounted commission fee. If the publisher wants to reduce the cost of getting high-quality data, he should increase his reputation. Moreover, the RE$_{pu}$ is also a weighting coefficient in a participant’s reputation updating (see Eq. (4)), so it can be an intrinsic motivation.

**4.3 From platform’s viewpoint: Condition of being profitable**

According to Table 2, the actual platform profit can be computed by Eq. (13):
\[
P_{\text{plat}} = \sum_{i=1}^{m_1} b_i \times p + m_3 \cdot n \cdot c - m_2 \cdot n \cdot c
\]

In order to make a platform profitable, we consider the worst scenario: All of the sensed data are bad quality, and the publisher gives a bad rating for these data truthfully. In this condition: $m_2 = m, m_1 = m_3 = 0$, and the platform profit becomes:
\[
P_{\text{plat}} = \sum_{i=1}^{m_2} b_i \cdot p - m_2 \cdot n \cdot c. \quad \text{(13)}
\]

One good way is to recruit an appropriate number of gamers with suitable rewards that satisfy $n \cdot c \leq \min\{b_i \cdot p\}$. Thus $P_{\text{plat}}$ is always a positive value. In practical cases, the reward to each gamer is always 0, for gamers are mainly looking for fun in gamification-based verification, and do not care about small rewards. Therefore, the platform is always profitable for $P_{\text{plat}} \geq P_{\text{worst}} \geq 0$.

**5 Conclusion**

Generally, an MCS system usually pertains to three stakeholders: task publishers, crowd participants, and a crowdsourcing platform. All these roles are rational, and attempt to maximize their utilities/profits. Therefore, incentive is a fundamental issue in MCS. However, most existing work only investigates the utilities from separate viewpoints of partial roles in MCS, i.e., a participant’s utility and/or a platform’s profit. This paper proposes an integrated incentive framework for MCS, which includes three components: a reverse-auction-based two-round participant selection mechanism, gamification-based verification of the publisher’s feedback regarding the quality of data provided by the crowd, and detailed procedures of reputation updating for the participants and publisher. Furthermore, we analyze the properties from the viewpoints of these three stakeholders, and infer that the integrated incentive mechanism framework can motivate participants to provide high-quality data, stimulate publishers to give truthful feedback, and make a platform profitable.

Our work can be extended in the following ways: Thorough experiments can be conducted to verify our theoretical results. Moreover, the proposed incentive
framework is still “off-line” and can only deal with static scenarios. It will be interesting to investigate how to accommodate dynamic factors in MCS systems (e.g., time constraints, individuals’ joining and leaving, etc.).

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