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Article

TB-HQ: An Incentive Mechanism for High-Quality Cooperation in Crowdsensing

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Abstract: Crowdsensing utilizes a range of sensing resources and participants, including mobile device sensors, to achieve collaborative sensing and information fusion. This enables it to handle complex social sensing tasks and provide more intelligent and real-time environment sensing services. Incentive mechanisms in crowdsensing are employed to address issues related to insufficient user participation and low-quality data submission. However, existing mechanisms fail to adequately consider reference points in user decision-making and uncertainty in the decision-making environment. This results in high incentive costs for the platform and limited effectiveness. On the one hand, the probabilities and utilities in the actual decision environment are defined based on user preferences, and uncertainty can lead to unpredictable impacts on users' future gains or losses. On the other hand, users identify their choices based on certain known values, namely reference points. The factors influencing user decisions are not solely the absolute final result level but rather the relative changes or differences between the final result and the reference point. Therefore, to resolve this problem, we propose TB-HQ, an incentive mechanism for high-quality cooperation in crowdsensing, which simultaneously considers the reference points adopted by users in decision-making and the uncertainty caused by their preferences. This mechanism includes a task bonus-based incentive mechanism (TBIM) and a high quality-driven winner screening mechanism (HQWSM). TBIM motivates users to participate in tasks by offering task bonuses, which alter their reference points. HQWSM enhances data quality by reconstructing utility functions based on user preferences. Simulation results indicate that the proposed incentive mechanism is more effective in improving data quality and platform utility than the comparative incentive mechanisms, with a 32.7% increase in data quality and a 77.3% increase in platform utility.

Keywords: sensor devices; incentive mechanism; data quality; crowdsensing

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1. Introduction

Crowdsensing utilizes the mobile devices of ordinary users as basic sensing units, enabling conscious or unconscious collaboration through the mobile internet to distribute sensing tasks and collect sensing data. This approach facilitates the completion of large-scale and complex social sensing tasks [1]. Therefore, attracting a large number of users to participate and incentivizing them to submit high-quality data are two crucial factors for the success of crowdsensing [2]. Numerous studies have been conducted on motivating users to participate in perception tasks to improve participation rates [3–6]. For instance, Ref. [3] analysed urban noise pollution in real-time by encouraging numerous mobile sensing users to participate in tasks that enhance sensing data. Several studies have been conducted on data quality indicators [7–9]. For example, Ref. [7] applied crowdsensing to the Internet of Vehicles and proposed a quality-aware incentive mechanism to collect sensory data related to the road environment, thereby improving traffic efficiency. In this context, data quality was measured by the sensing accuracy and the sensing range.

However, it is important to note that mobile devices consume power and traffic during data collection [1,2]. Ensuring that a large number of users provide high-quality services can be challenging for a crowdsensing platform. Therefore, to recruit enough users to participate and motivate them to provide high-quality data, a reasonable incentive mechanism is crucial.

In response to the given requirements, incentive mechanisms can be classified into two categories: monetary and non-monetary incentives [10–12]. Both types are based on the expected utility theory of traditional economics, which analyses the costs and benefits to the user in order to improve the perceived data quality and platform income. This type of decision-making model has the following two problems:

Firstly, it does not consider the impact of uncertainty caused by user preferences on user decision-making. Due to the heterogeneity in the distribution of task locations, participation costs, and user capabilities, such as computing power and sensing abilities [13], the outcome of their decision-making is unknown when users submit either high-quality or low-quality data. In this context, uncertainty affects the potential gains or losses of users. User preferences play a decisive role in determining the probabilities and utilities in the decision-making process [14]. Uncertainty is often not expressed as specific probabilities, and its outcomes are implicit costs that affect user decisions. Ignoring the impact of uncertainty means that users' actual utility values cannot reach their theoretical values.

Secondly, users make decisions based on relative changes or differences between the final outcome and a reference point, rather than absolute gains or losses. Therefore, to increase participation levels and data quality on crowdsensing platforms, it is necessary to increase cost investment [15–19]. It is important to note that individual users identify outcomes based on reference points, not the absolute final outcome level [20]. Therefore, users' gains or losses depend on whether the final chosen outcome is above or below the reference point. Existing incentive mechanisms only consider the impact on user decisions from absolute gains or costs, neglecting the constraints of reference points on users' final choices. This inevitably reduces the effectiveness of incentives.

In actual scenarios, the following two phenomena occur: First, in actual scenarios, the negative utility of losses to users is greater than the positive utility of equal gains [21]. Second, continued ownership increases users' valuations of the same item, so users tend to maintain the status quo [22]. For the sake of simplicity, this paper will refer to the above two phenomena as loss sensitivity and owner preference, respectively.

In the owner preference phenomenon, the user takes the state of ownership as the initial reference point; if the owned item is lost, the user is in a state of loss. According to the loss sensitivity phenomenon mentioned above, the disutility caused by the loss of an item is greater than the value of the item itself, suggesting that the user's original ownership of the item caused them to increase the value of the item. The loss sensitivity phenomenon is a reflection of user preference, indicating that users are more sensitive to equivalent losses than to gains.

This paper finds that the above two phenomena can optimize the problems of the existing incentive mechanism. First, based on the owner preference phenomenon, users are provided with task bonuses before they participate in tasks in crowdsensing so that users can improve their assessment of the value of task bonuses, and the initial reference point is adjusted so that users are unwilling to lose task bonuses and increase their level of task participation. Second, based on the performance of user preferences in the loss sensitive phenomenon, the remuneration of high-quality users is taken as the user's reference point, and a loss sensitive utility evaluation function is set up related to data quality to encourage users to improve data quality in order to avoid losing task bonuses. The optimization is based on real scenarios, aiming at the above two problems, modeling the characteristics of users making decisions based on reference points, and reflecting the influence of user preferences in the decision-making process.

In summary, the incentive mechanism proposed in this paper sets a task bonus that affects the user's initial state and a utility evaluation function that takes into account the user's preferences. Inspired by the phenomenon of owner preference, this paper proposes a cooperation guarantee mechanism TBIM based on task bonuses that influences users' willingness to participate in tasks based on their overestimation of task bonuses. Inspired by the loss sensitivity phenomenon, this paper proposes a high-quality data-driven winner selection mechanism, HQWSM, which uses users' different sensitivities to losses and gains to construct a utility evaluation function to encourage users to complete tasks with high-quality data. Table 1 is shown as follows:

Table 1. Study progression.

Mechanism	TBIM	HQWSM
Inspiration	Owner preference	Loss sensitive
Design	Issue task bonuses to users before they participate in tasks	Design utility evaluation functions related to data quality when users are engaged in tasks
Manifestation of Preference	Users increase their assessment of the value of held task bonuses	Users are more sensitive to loss of utility due to data quality
Reference Point	The status of the user holding the task bonus	Remuneration for users with the highest data quality
Decision-making Situation	Give up participating in the task, lose the task bonus, and the loss value is higher; Choose to participate in the task and keep the task bonus	Reduced data quality, increased distance from reference points, higher estimated damage value; Improve data quality, reduce distance from reference points, and reduce losses
Effect	Users are unwilling to give up task bonuses, thereby increasing willingness to participate	Users improve data quality to reduce bonus losses

This paper refers to TBIM and HQWSM collectively as TB-HQ. The main contributions of this paper are as follows:

- The paper proposes a cooperation guarantee mechanism based on the task bonus, and introduces the task bonus to adjust the user's reference point, taking advantage of the user's higher valuation of item ownership, and influences the user's willingness to participate in the task based on the user's own participation tendency and stickiness to the task bonus, thus encouraging users to actively participate in the task.
- The paper proposes a quality-driven winner screening mechanism. Aiming at the uncertainty caused by user preferences, we set task bonuses and avoidance utilities related to data quality, exploit users' higher sensitivity to losses, and propose a quality-oriented winner selection algorithm to encourage users to complete tasks with high-quality data.
- The paper verifies the effectiveness of TB-HQ, composed of TBIM and HQWSM, through simulation comparison experiments. We compare TB-HQ with mechanisms such as NMBIM. The results of the simulation experiments show that under the influence of TB-HQ, the user's data quality is improved by 32.7% and the platform utility is increased by 77.3% compared to the comparison mechanism. TB-HQ can effectively improve the data quality and utility of the platform.

The remainder of this paper is organized as follows: Section 2 describes related work. Section 3 provides a detailed description of the crowdsensing system model and describes a specific analysis of the design and characteristics of TB-HQ. Section 4 presents the experimental evaluation of TB-HQ. Finally, Section 5 concludes the paper.

2. Related Work

Extensive research has been conducted on incentive mechanisms for crowdsensing to motivate users to increase their participation and submit high-quality data.

In terms of improving the participation level, Ref. [23] calculated the probability of each user passing through different paths based on their collected historical trajectories. It then obtained the task set corresponding to each route, motivating participants in a targeted manner to maximize the expected social welfare. Ref. [10] motivated users to participate in tasks through a combination of monetary and non-monetary methods. Ref. [15] proposed an auction-based, budget-feasible mechanism called ABSee, which employs a greedy algorithm for participant selection. Ref. [24] used deep learning technology to accurately predict bicycle demand, effectively recruit participants from hybrid bicycle fleets, and assign tasks to participants in hybrid fleets with dynamic incentive design and reward expectations to find the optimal station rebalancing solution. Ref. [25] combined the multi-armed bandit algorithm and reverse auction to design an incentive mechanism for solving the problem of recruiting multiple unknown workers in mobile crowdsensing. Ref. [16] proposed a tensor-based truthful incentive mechanism to motivate vehicles to participate in completing tasks, ensuring the safety of the entire process and maximizing social welfare. Ref. [17] proposed an incentive mechanism based on reverse auction, using an approximate algorithm to select the winning bidder with almost minimum social cost to reduce platform costs and increase participation levels. Ref. [26] adopted a lowest-cost winner selection mechanism to reduce the social cost of winner selection while ensuring task quality requirements, select the most cost-effective winner, and use a critical payment determination mechanism to determine the winner's reward. Ref. [11] proposed a participant selection strategy based on dynamic incentives to calculate participant reliability. This was achieved by considering both the task completion rate and the task pass rate, which helped to address the issue of low platform participation levels. Ref. [27] improved the expected value of recruited participants under budget constraints through a combination of binary search and greedy heuristic solutions to ensure the expected performance of perceived outcomes.

In terms of improving data quality, ref. [28] utilized task allocation intelligent contracts to assign additional sensing tasks to users with higher reputation values, with the aim of obtaining high-quality sensing data. Ref. [7] designed an IRGAT model to capture the implicit and explicit relationships between grids through the dual-channel mechanism of relationship awareness and graph attention, and perform data reasoning on the collected data subset of the aware grid to improve its data quality. Ref. [18] proposed a freshness-aware incentive mechanism to recruit suitable mobile users, thereby optimizing the average information freshness and data quality while adhering to budget constraints. Ref. [29] selected low-cost, high-quality users to perform on-board crowd sensing tasks and update user reputation by evaluating the quality of the provided data. A correlation was observed between user reputation and reward distribution, which motivated users to continue providing high-quality data to increase rewards. Ref. [19] employed the Strutberg game to analyse the interaction between edge servers and vehicles in vehicle crowd sensing, and derived optimal bidding strategies for vehicles participating in sensing activities through multi-agent actor-critic neural networks to optimize task allocation for overall data quality. Ref. [30] motivated mobile users to maintain their reputation in task groups and ensure data quality and reliability by voting in a task group. Ref. [31] determined the rewards for users based on whether their solutions matched those of the majority, balancing solution quality and platform cost. Ref. [32] proposed EPRICE, a real-time incentive system designed to support the distribution of rewards based on quality. Ref. [12] combined fixed rewards and floating rewards to motivate users to submit high-quality data. Ref. [33] used blockchain to verify data quality in crowdsensing.

Although the studies mentioned above have improved and innovated the incentive mechanism from different perspectives, nonetheless, they have not considered certain issues.

Firstly, most research on incentive mechanisms does not properly take into account the impact of uncertainty caused by user preferences on user decisions [28–30]. Additionally, few incentive mechanisms that introduce uncertainty take into account user preferences and their associated probabilities. Users are incentivized with deterministic utility or combined with fixed probabilities [7,18,23,25]. For instance, Ref. [28] proposed a data pricing contract in which users adjust the salary price based on the price level of the previous period, that is, the salary price of the next round can be determined directly after the price level is determined. Ref. [29] combined user reputation and data quality to determine user remuneration. The reputation value gained by submitting high-quality data in each round was found to be equal to the reputation value reduced by submitting low-quality data. Ref. [30] relied only on data quality and compensation for judgement in the process of users maintaining reputation and voting for other users, and there was no uncertainty caused by user preferences. The crowdsensing scheme proposed by [7], which is based on the implicit relation perception graph attention network (CVC-IRGAT), uses static real datasets for data reasoning and does not consider uncertainty. Similarly, Ref. [25] modeled the worker recruitment process as a multi-armed bandit problem and also used a specific real dataset to determine the true cost and data quality of workers. Refs. [18,23] both derived probabilities from fixed historical information to recommend tasks to users. However, fixed probabilities cannot reflect the uncertainty caused by user preferences [14].

Secondly, the incentive mechanism described above motivates users to make decisions based on absolute gains or losses. The platform can only motivate users through higher rewards to obtain higher participation levels and data quality. For instance, the reward distribution mechanism in [10,19,26,32] is also based on absolute values. Refs. [28,29] determined rewards based on user reputation and data quality. Users can receive more rewards by aiming for higher reputation values and submitting higher-quality sensory data. In [26], user rewards were determined by the volume and quality of data they contributed through completed tasks. The greater the increase in data quality, the greater the benefits received. Ref. [27] attracted more participants only by designing absolute reward rules and screening mechanisms. Ref. [12] introduced floating rewards to improve the flexibility of rewards, but in essence these still constituted an absolute reward composition.

Compared to prior research, this paper considers both the reference points used by users in decision-making and the uncertainty resulting from user preferences. It proposes an incentive mechanism that is oriented towards participation levels and high-quality data.

3. System Design and Analysis

This section is divided into three parts. Section 3.1 briefly introduces the physical model of crowdsensing and the related concepts and logical processes. Sections 3.2 and 3.3 introduce the functional processes of TBIM and HQWSM in detail.

3.1. System Model

Section 3.1.1 introduces the MCS physical model and provides commonly used symbols and parameters. Section 3.1.2 explains the functional processes of TBIM and HQWSM through logic diagrams.

3.1.1. Physical Model

This subsection will now explain the physical model of the crowdsensing system. Please check the Abbreviation section below for the key symbols used in the full text, for ease of explanation.

The crowdsensing system consists of a cloud platform and many mobile users [34], as shown in Figure 1. This model considers the multi-turn relationships between a requester and multiple participants $W_u^l = \{1, 2, \ldots, n\}$. In each round $l \in N^+$, the requester can issue multiple tasks $\mathcal{R}^l = \{r_1, r_2, \ldots, r_m\}$, with r_j representing the jth task. The number of tasks released by a requester in the Round $l \in N^+$ is denoted by m. It is important to note that the type of each task is different, and both n and m are positive numbers. Each user $i \in W_u^l$ can select multiple tasks $\Gamma_i^l = \{(r_j, b_j) | j \leq m\}$, and a task can also be selected and executed by multiple users. $\widehat{W_{sel}^l} \in W_u^l$ represents the set of users who chose to participate in the Round $l \in N^+$.

The fundamental process of a crowdsensing system is delineated in Figure 1 as follows:

(1) Platform issues tasks $R^l = \{r_1, r_2, \ldots, r_m\}$ and task bonuses χ_i^l, representing the maximum reward values that each user can attain in each round. Users can acquire

task bonuses before opting to participate in tasks, updating the received reward values as reference points.

(2) Users submit participation strategies $\Gamma_i^l = \{(r_j, b_j) | j \leq m\}$, encompassing a list of tasks selected for participation and corresponding bids b_i. Upon receipt of task bonuses $\chi_{\rm i}^l$, users, influenced by the task bonus-based incentive mechanism (TBIM), make participation decisions that maximize their individual benefits, adjusting their assessments of task bonuses in response to reduced or vanished rewards.

(3) Platform selects winners $i \in W_{win}^l$ by comparing the ratio of historical quality information to bids for each participant and notifies the respective participants $i \in W_{sel}^l$.

(4) Winners $i \in W_{win}^l$ execute tasks and upload sensory data. During task execution, users compute the avoidance utility $\mathcal{R}(\Delta p_i^l)$ and, guided by the high quality-driven winner screening mechanism (HQWSM), select data quality updates to maximize their own utility, thereby avoiding losses in basic rewards $p_{\rm i}^l$ and task bonuses $\chi_{\rm i}^l$.

(5) Platform evaluates sensory data and disburses rewards. The platform assesses data provided by each winner, updates historical quality information for each participant, and subsequently pays out basic rewards and converted bonuses based on the data quality of winners.

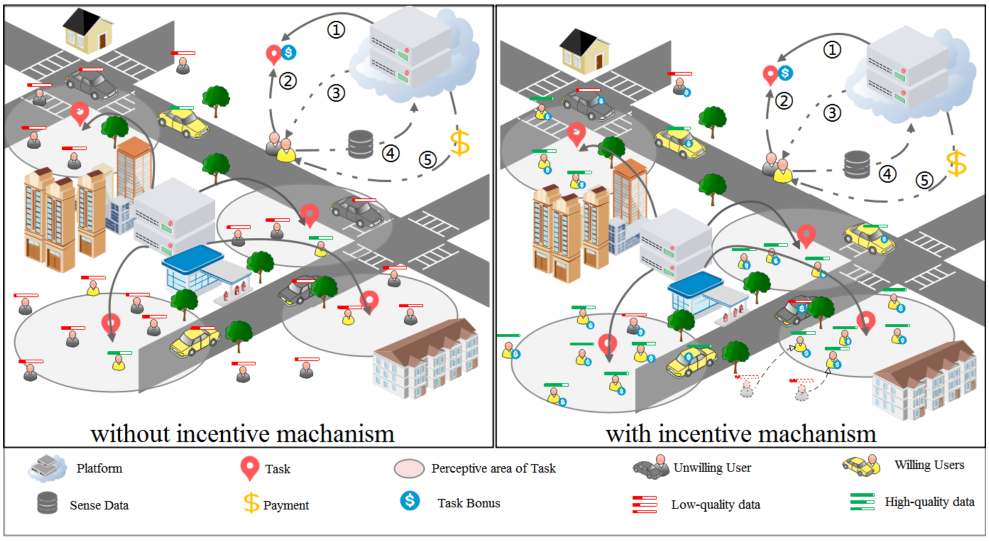


Figure 1. Physical model.

3.1.2. Logical Model

Next, we elaborate on the logical model of TB-HQ, comprising two components, TBIM and HQWSM, as illustrated in Figure 2.

For the sake of elucidating the logical diagram in Figure 2, we provide the following definitions:

Definition 1. *(Participation Potential ω_i^l). A scalar positively correlated with the willingness of a user selecting a task. A higher participation potential indicates a greater likelihood of a user choosing to participate in a task. When the participation potential exceeds a target threshold, the user decides to participate in the task.*

Definition 2. *(Propensity δ_l^l). The impact of user preferences on the participation potential.*

Definition 3. *(Stickiness Ω_i^1). The weighted ratio of a user's acquired task bonuses to costs, indicating the user's enthusiasm for participating in the task.*

Definition 4. *(Converted Bonus ℓ_i^l). The task bonus received by the user calculated based on their data quality.*

Definition 5. *(Loss Factor λ). The degree to which user preferences influence the loss of rewards, with $\lambda > 1$.*

Definition 6. *(Avoidance Utility $\mathcal{R}(\Delta p_i^l)$). The impact of data quality levels on user utility.*

These definitions lay the foundation for the subsequent explication of the logical model represented in Figure 2.

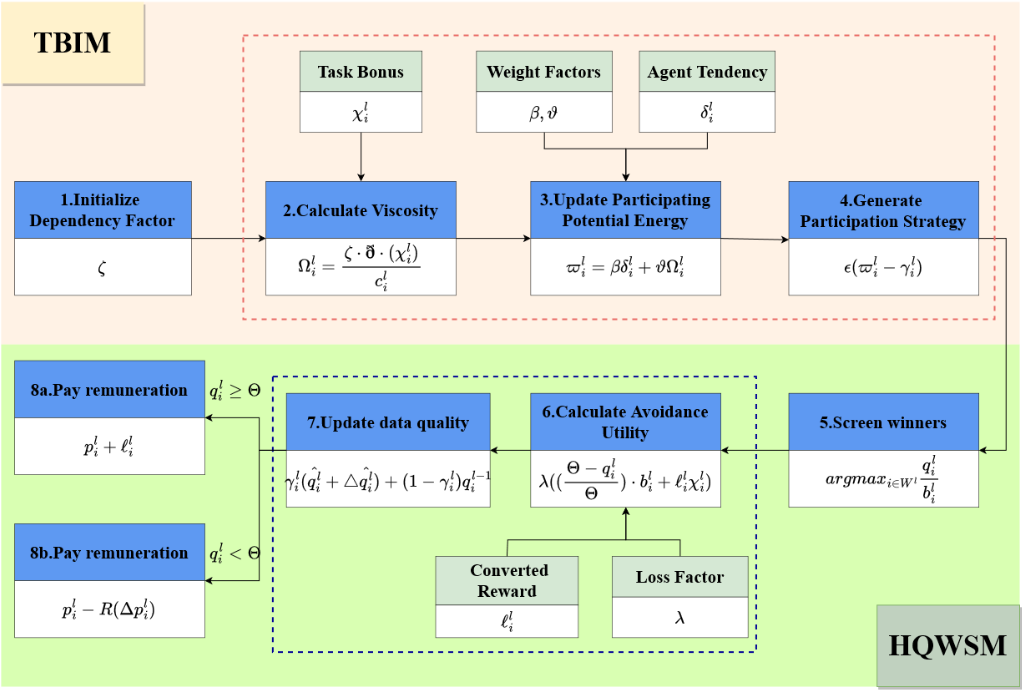


Figure 2. Design of logical framework for TBIM and HQWSM.

TBIM consists of steps 1, 2, 3, and 4 as depicted in Figure 2. In TBIM, the platform issues task bonuses χ_i^l and sets weight factors β, ϑ that influence user participation strategies, encouraging users to reassess their reference points of gains and losses. This leads to an elevation in users' participation potential ϖ_i^l, prompting them to select more tasks and consequently enhancing platform participation levels. In step 1, users initialize dependence factors ζ based on platform rules. In step 2, the platform releases tasks R^1 and task bonuses χ_1^l, and users calculate the stickiness Ω_i^l based on the dependence factors ζ from step 1. Step 3 involves updating participation potential ϖ_i^l based on weight factors β, ϑ and user propensities δ_i^l. Finally, in step 4, users generate participation strategies based on the participation potential obtained in step 3, selecting tasks and submitting bids. The platform then employs this information to screen winners for task participation.

HQWSM comprises steps 5, 6, 7, and 8. In HQWSM, the platform introduces avoidance utility $\mathcal{R}(\Delta p_i^l)$ to impact user utilities, incentivizing users to enhance the quality of uploaded data to become winners and receive higher rewards. Step 5 involves the platform selecting winners for task participation based on historical data quality and bids. In step 6, users selected as winners must adjust their avoidance utility $\mathcal{R}(\Delta p_i^l)$, considering converted bonuses ℓ_i^l and the loss factor λ. The adjustment, coupled with the data quality to be submitted and the quality threshold θ set by the platform, influences the user utility Π_i^l in this round. Step 7 sees users updating the quality of the uploaded data to attain higher rewards. Finally, in step 8, the platform evaluates the data submitted by users and settles rewards. At this point, there are two scenarios: (1) If users submit high-quality data, they receive basic rewards p_i^l and converted bonuses ℓ_i^l; (2) If the submitted data do not meet high-quality standards, users receive only basic rewards p_i^l. In this manner, the platform achieves an enhancement in data quality under the constraint of a limited budget.

3.2. Task Bonus-Based Incentive Mechanism

3.2.1. Construction of Participation Potential

This subsection primarily introduces the critical parameters involved in the mechanism and their calculations, laying the groundwork for the subsequent detailed explanation of the mechanism's specific operational processes.

In order to encourage more users to actively participate in tasks to achieve the quality required by the platform and maximize their own benefits, the platform stipulates that each participant can receive a basic reward based on the cost of performing the task, as well as a portion of the task bonus. In TBIM, the prepaid task bonus is used as an incentive strategy. This means that if a user has never received the task bonus, choosing not to participate in the task will not result in any gain or loss. However, once the user receives the task bonus, the reference point for gains and losses will shift. They will view giving up participation in the task as a loss, as it results in the reduction or loss of the task bonus [22]. The mechanism utilizes this to enhance users' assessment of their rewards, ultimately altering users' decisions to participate.

Various payment methods are available for sensing tasks in crowdsensing systems. For sensing tasks with budget constraints, the total payment amount is always predetermined. In order to obtain high-quality data with budget constraints, this paper stipulates that each user's remuneration includes basic consumption cost compensation, and a certain proportion ξ_i^l of task bonus $\xi_i^l \cdot \chi_i^l$, before choosing to participate in the task, where $\xi_i^l \in [0,1]$. If the user's participation status η_i^l is 0, they will not be required to pay any price and will also forfeit the task bonus. Similarly, if the user decides to participate, their participation status η_i^l will be marked as 1 and the total reward at that point will be calculated using Formula (1).

$$p_i^l = c_i^l + \eta_i^l(\xi_i^l \cdot \chi_i^l) \tag{1}$$

Based on the above, the revenue relationship between the platform and users is as follows: (1) If the user chooses to cooperate with the platform, both parties earn income $((\psi_v^l - p_i^l), (c_i^l + \eta_i^l(\xi_i^l \cdot \chi_i^l)))$. (2) If the platform chooses to cooperate but the user refuses, both parties earn income $((-p_i^l), 0)$.

When users cooperate with the platform, the platform needs to provide additional compensation in exchange for data. Users should be appropriately rewarded for providing valid data, and they will only choose to cooperate if their participation potential exceeds the participation threshold.

We will now examine how task bonuses impact users' participation preferences while under the influence of TBIM. When a user does not participate in a task, the evaluation value of their task bonus χ_i^l is higher than the actual value lost. Following Formula (1), we set the evaluation value to V_i^l, as shown in Formula (2), where $\eth \geq 1$ represents the user's amplification factor for task bonuses. Formula (2) is derived from [22].

$$V_i^l = \eth \cdot \left(\chi_i^l\right)^+ \tag{2}$$

The platform offers task bonuses χ_i^l to users prior to their provision of data, cultivating users' stickiness to task bonuses. Considering the impact of the evaluation value V_i^l and the user's own consumption cost on the user's decision-making participation, and that the greater the user's evaluation value of the task bonus, the greater the stickiness to the task, and that as the user's own consumption cost increases, the stickiness will become smaller, we set the stickiness as shown in Formula (3):

$$\Omega_i^l = \frac{\zeta \cdot V_i^l}{c_i^l} \tag{3}$$

where $\zeta \in (0,1)$ represents the dependence factor. The larger the value, the greater the impact of the task bonus on the stickiness of users participating in the task.

The main factors influencing a user's decision to participate in a task are their tendency to participate and the stickiness of the task bonus. Therefore, the user's participation potential is represented as Formula (4):

$$\varpi_i^l = \beta\delta_i^l + \vartheta\Omega_i^l \tag{4}$$

where β, ϑ represent the weight of the participant preference and dependence on task bonuses, respectively. It is important to note that β and ϑ must satisfy the condition $\beta + \vartheta = 1$. If $\beta > \vartheta$, it indicates that user preference has a greater impact on the decision to participate than the dependence on task bonuses. Conversely, if $\beta < \vartheta$, it indicates that the influence of user preference is less than the dependence on task bonuses.

3.2.2. Calculation of Weight Factors

To discuss the impact of β, ϑ on the user participation potential ϖ_i^l, we use Algorithm 1 to find the parameter values that maximize ϖ_i^l. The first line calculates the potential when β falls within a certain range. Line 2 calculates each user's stickiness to the task bonus. Line 3 calculates the initial value of the participation potential. Lines 4–5 determine the value of β that maximizes the participation potential. Line 7 identifies β, ϑ that optimize the participation potential.

Algorithm 1 Calculation of weight factors for participating potential.

Input: $\delta_i^l, \varpi_i^{max} \leftarrow 0$
Output: β, ϑ
1: **for** $\beta = 0 \rightarrow 1$ **do**
2: $\quad\Omega_i^l \leftarrow \zeta \cdot V_i^l / c_i^l$
3: $\quad\varpi_i^l \leftarrow \beta\delta_i^l + \vartheta\Omega_i^l$
4: $\quad$**if** $\varpi_i^l > \varpi_i^{max}$ **then**
5: $\qquad\varpi_i^{max} \leftarrow \varpi_i^l$
6: $\quad$**end if**
7: $\quad\vartheta = 1 - \beta$
8: **end for**
9: **return** β, ϑ

Formula (4) shows that the participation potential of each user depends not only on their own tendency δ_i^l and Ω_i^l, but also on the weight of other users. Therefore, the weight value is crucial for the user's potential participation. The influence of the weight factors β, ϑ on the user participation potential energy is proven using Theorem 1.

Theorem 1. *If* $\chi_i^{before} > \chi_i^{after}$ *and* $\delta_i^{before} < \delta_i^{after}$, $\exists\beta \in (0,1), \exists\vartheta \in (0,1), \varpi_i^{before} > \varpi_i^{after}$.

Proof of Theorem 1. Formula (3) states that if $\chi_i^{before} > \chi_i^{after} > 0$, the user's stickiness to the task bonus is $\Omega_i^{before} > \Omega_i^{after} > 0$. Assuming that $\delta_i^{before} = \tau\delta_i^{after}, \Omega_i^{before} = (1/\epsilon)\Omega_i^{after}$, then $\beta\delta_i^{before} = \beta\tau\delta_i^{after}, \vartheta\Omega_i^{before} = \vartheta(1/\epsilon)\Omega_i^{after}$, according to $\varpi_i^{before} = \beta\delta_i^{before} + \vartheta\Omega_i^{before}$, $\varpi_i^{before} = \beta\tau\delta_i^{after} + \vartheta(1/\epsilon)\Omega_i^{after}$. And $\varpi_i^{after} = \beta\delta_i^{after} + \vartheta\Omega_i^{after}$, so $\varpi_i^{after} = \beta(\tau-1)\delta_i^{after} - \vartheta((\epsilon-1)/\epsilon)\Omega_i^{after}$. If $\beta(\tau-1)\delta_i^{after} - \vartheta((\epsilon-1)/\epsilon)\Omega_i^{after} > 0$, then $\beta(\tau-1)\delta_i^{after} - \vartheta((\epsilon-1)/\epsilon)\Omega_i^{after} > 0$. As $\beta = 1 - \vartheta$, we can deduce that $(1-\vartheta)\epsilon(\tau-1)\delta_i^{after} - \vartheta(\epsilon-1)\Omega_i^{after} > 0$, leading to $\epsilon(\tau-1)\delta_i^{after} < 0$ and $(\epsilon-1)\Omega_i^{after} < 0$. This satisfies the equation $0 < \frac{\epsilon(\tau-1)\delta_i^{after}}{\left(\epsilon(\tau-1)\delta_i^{after} + (\epsilon-1)\Omega_i^{after}\right)} < \vartheta$, indicating that $\beta = 1 - \vartheta < 1$. Theorem 1 is proved. □

Theorem 1 demonstrates that a user's decision to participate is influenced by the weight factors of the user's own tendency and the evaluation value of the task bonus. In summary, the platform can enhance the user's participation potential by offering task bonuses prior to their decision to participate in the task.

3.2.3. Cooperation Guarantee Mechanism

The influence of task bonuses on users' participation decisions increases the likelihood of cooperation. The impact of task bonuses on user participation in cooperation is analyzed using Theorem 2.

Theorem 2. *When the dependency factor ζ satisfies $\frac{(\gamma_i^l - \beta min(\delta_i^l))c_i^l}{\vartheta\left(\eth\cdot(\chi_i^l)^+\right)} \le \zeta < \frac{1}{2}$, the user is more likely to choose to participate in cooperation.*

Proof of Theorem 2. Formula (4) shows that if $\beta(\delta_i^l) > \gamma_i^l$, meaning that the user's own tendency δ_i^l is always greater than its own participation selection threshold γ_i^l before and after adding task bonus χ_i^l, the user will choose to participate in the auction activity before and after adding the task bonus. When $\beta(\delta_i^l) < \gamma_i^l$, $\left(\gamma_i^l - \beta(\delta_i^l)\right)/\vartheta\left(\eth\cdot(\chi_i^l)^+/c_i^l\right) > 0$ always holds. After adding the task bonus, if the inequality $\left(\gamma_i^l - \beta(\delta_i^l)\right)/\vartheta\left(\eth\cdot(\chi_i^l)^+/c_i^l\right) > \zeta > 0$ (i.e., $\gamma_i^l > \zeta\vartheta\left(\eth\cdot(\chi_i^l)^+/c_i^l\right) + \beta(\delta_i^l) > 0$) always holds, it means that adding the task bonus has no impact on the user's participation choice. In the same way, when $\beta(\delta_i^l) < \gamma_i^l$, after adding the task bonus, if the inequality $\zeta > \left(\gamma_i^l - \beta(\delta_i^l)\right)/\vartheta\left(\eth\cdot(\chi_i^l)^+/c_i^l\right) > 0$ holds, then the dependence factor must at least satisfy $\zeta > \left(\gamma_i^l - \beta min\left(\delta_i^l\right)\right)\Big/\vartheta\left(\eth\cdot\left(\chi_i^l\right)^+\Big/c_i^l\right) > 0$ to satisfy $\gamma_i^l < \zeta\left(\eth\cdot(\chi_i^l)^+\Big/c_i^l\right) + \beta(\delta_i^l)$, indicating that the task bonus motivates users to choose cooperation. Theorem 2 is proved. □

Theorem 2 proves that the task bonus increases the possibility of user participation. This paper will analyse how the mechanism affects users' decision-making regarding participation.

TBIM introduces the concept of participation potential ϖ_i^l and compares each user's participation potential energy with its target threshold γ_i^l. If the user's participation potential exceeds the target threshold, they will choose to participate in the task. Otherwise, they will decline to participate. Regarding the specific process of how users choose to participate or not, this paper provides Algorithm 2, as shown below.

Algorithm 2 User participation decision-making algorithm.

Input: $\delta_i^l, c_i^l\chi_i^l, \gamma_i^l$
Output: $\widehat{W_{sel}^l}$

```
for each i ∈ W_u^l do
    Grand task bonuses χ_i^l
    Update the Evaluation Value V_i^l ← ð · (χ_i^l)^+
end for
for each i ∈ W_u^l do
    Ω_i^l ← ζ · V_i^l / c_i^l
    ϖ_i^l ← βδ_i^l + ϑΩ_i^l
end for
while i ∈ W_u^l ∧ ϖ_i^l > γ_i^l do
    Ŵ_sel^l ← Ŵ_sel^l ∪ i
end while
return Ŵ_sel^l
```

3.3. High Quality-Driven Winner Screening Mechanism

3.3.1. Allocation of Rewards Based on Quality

This paper evaluates quality based on [15]. The user's quality score in round l is $\check{q}_i^l$. The platform's revenue ψ_p^l increases with higher quality scores. If a user participates multiple times, their historical data quality update method in the first l rounds is as follows:

$$q_i^l = \gamma_i^l \widehat{q_i^l} + (1 - \gamma_i^l) q_i^{l-1},\ i \in \widehat{W_{sel}^l} \tag{5}$$

where the constant γ_i^l represents the weight of the user's data quality in round l. At the same time, the paper also considers the impact of the user's historical data quality on the user's total quality, and the weight is $1 - \gamma_i^l$.

In general, when multiple participants compete for the same task, the probability of winning increases with higher quality. Therefore, this paper proposes a winner screening mechanism, which is presented in Algorithm 3. $\widehat{W_{sel}^l}$ represents the group of users whose social welfare is greater than zero. $\widehat{W_{win}^l}$ refers to the initial users, and $\widehat{W_{win}^l}$ refers to the group of selected winners. The input for our system includes the user's bids b_i^l, the historical quality q_i^l, the number of selected tasks, the platform's budget B, and the task bonus χ^l. The output is the winner set $\widehat{W_{win}^l}$, $\widehat{W_{win}^H}$, $\widehat{W_{win}^L}$. The first step involves filtering out participants whose contribution value exceeds the reward for joining the set $\widehat{W_{sel}^l}$, as outlined in lines 2–6. Following this, line 7 arranges the tasks $r_j \in \mathcal{R}^l$ in descending order based on their quality threshold. Lines 8–14 introduce the pre-winner set $\widehat{W_{win}^l}$ based on the historical quality information and bids for all users $i \in \widehat{W_{sel}^l}$ who selected the task $r_j \in \mathcal{R}^l$. Line 11 calculates the user ID with the largest value and assigns it to x_i, while line 13 calculates the remaining quality requirements of the task r_j. The traversal continues until all users $i{:}r_j \in \Gamma_i^l, i \in \widehat{W_{sel}^l}$ are covered or the threshold $Q_{r_j \in \mathcal{R}^l}$ specified for each task is met before the end of the traversal. For the pre-winner set user $\widehat{W_{win}^l}$, lines 15–21 determine whether they should join the final winner set $\widehat{W_{win}^l}$ based on their basic remuneration under the budget constraint. Lines 18 and 20 compare the user's quality with the quality threshold specified by the platform and add it to $\widehat{W_{win}^H}$ and $\widehat{W_{win}^L}$, respectively. The final 23 lines return set $\widehat{W_{win}^l}$.

Next, this paper uses Theorem 3 to illustrate the budget rationality of the mechanism in the case of spending task rewards.

Theorem 3. *The mechanism satisfies budget rationality.*

Proof of Theorem 3. As per lines 15–19 in Algorithm 3, the total basic rewards paid to all winners must satisfy $\sum_{i \in \widehat{W_{win}^l}} b_i < (B - \chi)$. For the task bonus χ, when user $i \in \widehat{W_{win}^H}$, $\sum_{i \in \widehat{W_{win}^l}} \ell_i^l$
$= \sum_{i \in \widehat{W_{win}^l}} \left(\left(q_i^l - \theta \right) / \sum_{j \in \widehat{W_{win}^l}} q_i^l \right) \cdot \chi_i^l = \left(\left(\sum_{j \in \widehat{W_{win}^l}} q_i^l - \left| \widehat{W_{win}^l} \right| \theta \right) / \sum_{j \in \widehat{W_{win}^l}} q_i^l \right) \cdot \chi_i^l < \chi$, as shown in line 6 of Algorithm 3. Therefore, the compensation for all winners satisfies the condition $\sum_{i \in \widehat{W_{win}^l}} p_i < B$. The mechanism meets the requirement of budget rationality. Theorem 3 is proved. □

Algorithm 3 Winner screening algorithm.

Input: $b_i^l, \widehat{W_{sel}^l}, q_i^l, B, \left|\Gamma_i^l\right|, \chi^l, Q_{r_j \in \mathcal{R}^l}$

Output: $\widehat{W_{win}^l}, \widehat{W_{win}^H}, \widehat{W_{win}^L}$

$\widehat{W_{sel}^l} \leftarrow \varnothing, \widehat{W_{\omega in}^l} \leftarrow \varnothing, i \leftarrow i+1, k \leftarrow 1$

for each $i \in \widehat{W_{sel}^l}$ **do**

  if $\Phi(i) - b_i^l > 0$ **then**

    $\widehat{W_{sel}^l} \leftarrow \widehat{W_{sel}^l} \cup i$

  end if

end for

Sort all $r_j \in \mathcal{R}^l$ in descending order of $Q_{r_j \in \mathcal{R}^l}$

for each $r_j \in \mathcal{R}^l$ and $Q_{r_j \in \mathcal{R}^l} \neq 0$ **do**

  for all $i{:}r_j \in \Gamma_i^l, i \in \widehat{W_{sel}^l}$ **do**

    sort i in descending order of q_i^l / b_i^l

    $x_i \leftarrow argmax_{i:r_j \in \Gamma_i^l, i \in \widehat{W_{sel}^l}} q_i^l / b_i^l$

  end for

  $\widehat{W_{win}^l} \leftarrow \widehat{W_{win}^l} \cup \{x_i\}, Q_{r_j \in \mathcal{R}^l} \leftarrow Q_{r_j \in \mathcal{R}^l} - \min\left\{Q_{r_j \in \mathcal{R}^l}, q_{x_i}^l\right\}$

end for

while $i \in \widehat{W_{win}^l}$ **do**

  if $\sum_{i \in W_{win}^l} b_i < (B - \chi)$ **then**

    if $q_i^l > \theta$ **then**

      $\widehat{W_{win}^H} \leftarrow \widehat{W_{win}^H} \cup \{i\}, i \leftarrow i+1$

    else

      $\widehat{W_{win}^L} \leftarrow \widehat{W_{win}^L} \cup \{i\}, i \leftarrow i+1$

    end if

  end if

end while

return $\widehat{W_{win}^l} \leftarrow \widehat{W_{win}^H} \cup \widehat{W_{win}^L}$

According to Algorithm 3, if users want to increase the probability of becoming a winner, they need to improve the data quality. If the user's uploaded data quality exceeds the platform's specified quality threshold θ (i.e., $q_i^l > \theta$), it will be added to the high-quality winner set $\widehat{W_{win}^H}$. The basic reward p_i^l and task bonus χ_i^l will then be paid according to Formulas (6) and (7). To promote high-quality user participation, the platform will use a payment ratio of ℓ_i^l for task bonus payments using the payment method. Currently, the greater the disparity between the user's data quality and the quality threshold established by the platform, the higher the task bonuses earned.

$$p_i^l = b_i^l + \ell_i^l,\ i \in \widehat{W_{\omega in}^H} \tag{6}$$

$$\ell_i^l = \left(\frac{q_i^l - \theta}{\sum_{j \in \widehat{W_{win}^l}} q_i^l} \right) \cdot \chi_i^l \tag{7}$$

When user $i \in \widehat{W_{sel}^l}$ uploads data with a quality score of $q_i^l < \theta$, they are added to the low-quality set $\widehat{W_{win}^L}$. To incentivize low-quality users to participate in high-quality work in the next round (round $l+1$), a proportion of their remuneration will be paid according to Formula (8).

$$p_i^l = \left(\frac{q_i^l}{\theta}\right) \cdot b_i^l,\ i \in \widehat{W_{win}^L} \tag{8}$$

The algorithm for remuneration payment for this paper is as follows: The input for this round includes the winner set $\widehat{W_{win}^l}$, the task bonus χ^l set by the platform, and the user's quality q_i^l in round l. The output is the total payment P^l. In Algorithm 4, lines 1–3 calculate the basic consumption cost of each winner $i \in \widehat{W_{win}^L}$. For each winner, the final converted bonus ℓ_i^l and the total payment P^l will be paid based on whether the data quality provided meets the quality threshold. The sum of all winners' payouts is then returned on line 12.

Algorithm 4 Algorithm for remuneration payments.

Input: $\widehat{W_{win}^l}, \widehat{W_{win}^H}, \widehat{W_{win}^L}, \chi^l, q_i^l$
Output: P^l

1: **for** each $i \in \widehat{W_{win}^l}$ **do**
2: $\quad b_i^l = c_i^l \leftarrow \varphi_i \left|\Gamma_i^l\right|$
3: **end for**
4: **while** $i \in \widehat{W_{win}^l}$ **do**
5: $\quad$ **if** $i \in \widehat{W_{win}^H}$ **then**
6: $\quad\quad \ell_i^l \leftarrow (q_i^l - \theta)/(\sum_{j\in\widehat{W_{win}^l}} q_i^l) \cdot \chi_i^l$
7: $\quad\quad p_i^l \leftarrow b_i^l + \ell_i^l$
8: $\quad$ **else if** $i \in \widehat{W_{win}^L}$ **then**
9: $\quad\quad p_i^l = \left(q_i^l/\theta\right) \cdot b_i^l$
10: $\quad$ **end if**
11: $\quad i \leftarrow i+1$
12: **end while**
13: $P^l \leftarrow \sum_{j\in\widehat{W_{win}^l}} p_i^l$
14: **return** P^l

3.3.2. User Avoidance Utility

This paper introduces the loss factor λ, as defined in [21], to represent the impact of user preferences on loss. It then analyses the impact of the avoidance utility on user data quality. According to Formula (8), we set q_i^l/θ to α_i^l. $(\alpha_i^l \cdot \chi_i^l|_{loss})$ represents the user's perceived loss after receiving the task bonus. $(\alpha_i^l \cdot \chi_i/l|_{gain})$ represents the value lost by the user, where $(\alpha_i^l \cdot \chi_i^l|_{loss}) = \lambda(\alpha_i^l \cdot \chi_i^l|_{gain})$. As the user places more weight on loss than gain [21], this paper sets the loss factor $\lambda > 1$, resulting in $(\alpha_i^l \cdot \chi_i^l|_{loss}) > (\alpha_i^l \cdot \chi_i^l|_{gain})$. In order to avoid losses, users will choose to meet the quality threshold specified by the platform, and the mechanism will achieve the incentive purpose.

The following is a detailed analysis of the relationship between user data quality and their utility. This paper sets the avoidance utility $\mathcal{R}(\Delta p_i^l)$ to represent the impact of data quality on user utility. Formulas (9) and (10) are derived from [35]. When user $i \in \widehat{W_{win}^H}$, avoidance utility $\mathcal{R}(\Delta p_i^l) = 0$. If the user's data quality falls below the platform's set threshold ($i \in \widehat{W_{win}^L}$), they will use the reward $p_i^l = b_i^l + (maxq^l_{j_{j\in\widehat{W_{win}^H}}} - \theta)/(\sum_{j\in\widehat{W_{win}^l}} q_j^l) \cdot \chi_i^l$ received by the winner with the highest data quality as their adaptation level. The actual reward they receive $p_i^l = \left(q_i^l/\theta\right) \cdot b_i^l$ will be considered a loss. Currently, the loss of user

$i \in \widehat{W_{win}^{L}}$ is calculated as the difference Δp_i^l between their actual reward and that of the high-reward participant, as demonstrated in Formula (9).

$$\Delta p_i^l = \left(\frac{\theta - q_i^l}{\theta}\right) \cdot b_i^l + \frac{(maxq^l_{j_{j\in\widehat{W_{win}^{H}}}} - \theta)}{(\sum_{j\in\widehat{W_{win}^{l}}} q_j^l)} \cdot \chi_i^l \tag{9}$$

Currently, user $i \in \widehat{W_{win}^{L}}$ should bear the actual disutility of $\lambda\left(\Delta p_i^l\right)^{\varepsilon}$. Therefore, the avoidance utility $\mathcal{R}(\Delta p_i^l)$ can be represented by Formula (10).

$$\mathcal{R}\left(\Delta p_i^l\right) = \begin{cases} \lambda \cdot \left(\Delta p_i^l\right)^{\varepsilon} & , i \in \widehat{W_{win}^{L}} \\ 0 & , i \in \widehat{W_{win}^{H}} \end{cases} \tag{10}$$

Formula (11) displays the utility of each user $i \in \widehat{W_{win}^{l}}$. However, when user $i \in \widehat{W_{win}^{L}}$, their utility function is no longer solely based on economic gain, but also takes into account their avoidance utility.

$$U_i = \begin{cases} p_i^l - c_i^l + \ell_i^l & , i \in \widehat{W_{win}^{H}} \\ p_i^l - c_i^l - \mathcal{R}(\Delta p_i^l) & , i \in \widehat{W_{win}^{L}} \end{cases} \tag{11}$$

In summary, it can be seen that the user utility function is Formula (12):

$$\Pi_i^l = \begin{cases} b_i^l - c_i^l + \left(\frac{q_i^l - \theta}{\Sigma_{j\in\widehat{W_{win}^{l}}} q_i^l}\right) \cdot \chi_i^l & , i \in \widehat{W_{win}^{H}} \\ \left(\frac{q_i^l}{\theta}\right) \cdot b_i^l - c_i^l - \lambda \cdot \left(\left(\frac{\theta - q_i^l}{\theta}\right) \cdot b_i^l + \left(\frac{maxq^l_{j_{j\in\widehat{W_{win}^{H}}}} - \theta}{\Sigma_{j\in\widehat{W_{win}^{l}}} q_i^l}\right) \cdot \chi_i^l\right)^{\varepsilon} & , i \in \widehat{W_{win}^{L}} \end{cases} \tag{12}$$

At present, as user $i \in \widehat{W_{win}^{l}}$, improving its data quality will increase its utility. This is specifically analysed in Theorem 4.

Theorem 4. *For any user $i \in \widehat{W_{win}^{l}}$, the higher the quality of the user in a round (i.e., $q_i^{after} > q_i^{before}$), the greater the utility Π_i^l.*

Proof of Theorem 4. In order to prove the theorem, this paper will discuss the following two situations.

Case 1: When user $i \in \widehat{W_{win}^{H}}$, their converted bonus is $\ell_i^l = \left(\frac{q_i^l - \theta}{\Sigma_{j\in\widehat{W_{win}^{l}}} q_i^l}\right) \cdot \chi_i^l$. When $q_i^{after} > q_i^{before}$, $q_i^{after} - \theta > q_i^{before} - \theta$ is satisfied. So, $\chi_i^{after}\left(\left(q_i^{after} - \theta\right)/\Sigma_{j\in\widehat{W_{win}^{l}}} q_i{}^{after}\right) > \chi_i^{before}\left(\left(q_i^{before} - \theta\right)/\Sigma_{j\in\widehat{W_{win}^{l}}} q_i^{before}\right)$, and $\ell_i^{after} > \ell_i^{before}$, $\Pi_i^{after} > \Pi_i^{before}$. It can be seen that as the quality of user data improves, the more task bonuses are obtained and the utility gradually increases.

Case 2: For $i \in \widehat{W_{win}^{L}}$, $\Pi_i^l = \left(\frac{q_i^l}{\theta}\right) \cdot b_i^l - c_i^l - \lambda \cdot \left(\left(\frac{\theta - q_i^l}{\theta}\right) \cdot b_i^l + \left(\frac{maxq^l_{j_{j\in\widehat{W_{win}^{H}}}} - \theta}{\Sigma_{j\in\widehat{W_{win}^{l}}} q_i^l}\right) \cdot \chi_i^l\right)^{\varepsilon}$.

Upon taking the first derivative, it satisfies $\frac{\partial \Pi_i^l}{\partial q_i^l} = \frac{b_i^l}{\theta} - \lambda \cdot \varepsilon \cdot \left(-\frac{b_i^l}{\theta} - \frac{maxq^l_{j_{j\in\widehat{W_{win}^{H}}}} - \theta}{\left(\Sigma_{j\in\widehat{W_{win}^{l}}} q_j^{l^2}\right)} \cdot \chi_i^l\right)^{\varepsilon - 1}$.

At this point, as $\lambda > 1, \varepsilon > 0$, the first derivative $\frac{\partial \Pi_i^l}{\partial q_i^l}$ is greater than 0. If the user's data quality does not meet the threshold, i.e., $\theta > q_i^{after} > q_i^{before}$, its usefulness increases in proportion to the user's quality q_i^l. If the user's data quality improves beyond the platform's specified threshold, i.e., $q_i^{after} > \theta > q_i^{before}$, according to Formula (8), the user's utility Π_i^l is always greater than zero. Theorem 4 is proved. □

To summarize, winners $i \in \widehat{W_{win}^l}$ can maximize their utility by improving data quality q_i, while winners $i \in \widehat{W_{win}^L}$ can minimize their avoidance utility and maximize their overall utility by doing the same.

3.3.3. Data Quality Update

Formula (11) shows that users will reduce their avoidance utility $\mathcal{R}(\Delta p_i^l)$ to minimize the loss value Δp_i^l and maximize their user utility U_i when participating in the next round. This will encourage them to put in more effort to improve data quality during task performance. Formula (13) models the changes in user data quality in round l, considering the impact of avoidance utility.

$$\Delta \widehat{q_i^l} = \left(\left(maxq_j^{l-1}{}_{j \in \widehat{W_{win}^H}} - q_j^{l-1} \right) / \theta \right) \cdot \chi_i^l,\ i \in \widehat{W_{sel}^l} \tag{13}$$

Afterwards, the user's data quality is updated in the following round according to Formula (14).

$$q_i^l = \gamma_i^l \left(\widehat{q_i^l} + \Delta \widehat{q_i^l} \right) + (1 - \gamma_i^l) q_i^{l-1},\ i \in \widehat{W_{sel}^l} \tag{14}$$

Finally, Formula (11) shows that when winner $i \in \widehat{W_{win}^L}$ belongs to a low-quality domain, the higher the quality of its perceived data, the smaller the difference with the quality threshold set by the platform, and the smaller the avoidance utility it generates. It is specifically proved by Theorem 5.

Theorem 5. *For any winner $i \in \widehat{W_{win}^L}$, if the data quality it provides is higher (i.e., $\widehat{q_i^l}^{after} > \widehat{q_i^l}^{before}$),$\mathcal{R}(\Delta p_i^{after}) < \mathcal{R}(\Delta p_i^{before})$.*

Proof of Theorem 5. When user $i \in \widehat{W_{win}^L}$, if $\theta > \widehat{q^l}_{iafter} > \widehat{q^l}_{ibefore}$, then $\theta - \widehat{q^l}_{iafter} > \theta - \widehat{q^l}_{ibefore}$. And $\Delta p_i^{after} = \left(\frac{\theta - q_i^{after}}{\theta} \right) \cdot b_i^l + \left(\frac{maxq_j^{after}{}_{j \in \widehat{W_{win}^H}} - \theta}{\sum_{j \in \widehat{W_{win}^l}} q_i^l} \right) \cdot \chi_i^l$,$\Delta p_i^{before} = \left(\frac{\theta - q_i^{before}}{\theta} \right) \cdot b_i^l + \left(\frac{maxq_j^{before}{}_{j \in \widehat{W_{win}^H}} - \theta}{\sum_{j \in \widehat{W_{win}^l}} q_i^l} \right) \cdot \chi_i^l$. As $\lambda > 1, \varepsilon > 0$, $\mathcal{R}(\Delta p_i^l)$ is a monotonically increasing function of Δp. Therefore, $\mathcal{R}(\Delta p_i^{after}) < \mathcal{R}(\Delta p_i^{before})$. At present, $\mathcal{R}(\Delta p_i^l)$ decreases as the user's data quality improves, resulting in the maximization of user utility. If $\widehat{q^l}_{iafter} > \theta > \widehat{q^l}_{ibefore}$, then $\mathcal{R}(\Delta p_i^{after}) = 0 < \mathcal{R}(\Delta p_i^{before})$. Theorem 5 is proved. □

Theorem 4 determines that users aim to both maximize economic benefits and minimize the avoidance utility caused by losses through improving their data quality.

After participating in round l of the perception task, the winner combines the quality of the previous $l-1$ rounds to calculate the total quality of the first l rounds. The update method is shown in Algorithm 5. The input consists of the quality q_i^{l-1} of the first $l-1$ rounds completed by user i, the quality $\widehat{q_i^l}$ of the round l, and the task bonus χ_i^l. The output is the total quality q_i^l of the first l rounds completed by user i. In round l, all users will improve their own data quality based on the historical quality of other users, due to task bonuses and avoidance utility. If the user is participating in the auction for the first time, set their data quality value according to line 2. For users participating multiple times, calculate the change in data quality for user i in round l on line 6. Then, update the data quality on line 10.

Algorithm 5 Updating data quality.

Input: $\chi^l, q_i^{l-1}, \widehat{q_i^l}$
Output: q_i^l
1: **if** $i \in \widehat{W_{sel}^l}$ is a new participant **then**
2: Initialize q_i^l
3: **end if**
4: **for** all $i \in \widehat{W_{win}^l}$ **do**
5: **if** $i \in \widehat{W_{sel}^l}$ **then**
6: $\Delta\widehat{q_i^l} = \left(\left(maxq_j^{l-1}{}_{j\in\widehat{W_{win}^H}} - q_j^{l-1}\right)/\theta\right) \cdot \chi_i^l$
7: **end if**
8: **end for**
9: **for** all $i \in \widehat{W_{win}^l}$ **do**
10: $q_i^l = \gamma_i^l\left(\widehat{q_i^l} + \Delta\widehat{q_i^l}\right) + (1-\gamma_i^l)q_i^{l-1}$
11: **end for**
12: **return** $q^l_{i\in\widehat{W_{win}^l}}$

This paper refers to [15], and defines the platform utility as the difference between the sum of the actual contribution value $\phi(i)$ of each winner $i \in \widehat{W_{win}^l}$ and the remuneration paid to all winners. Formula (15) shows the calculation, which takes into account the contribution value of each winner, as well as the number of tasks selected and the data quality. The platform's revenue increases with higher data quality. u_i is the sum of the weights of tasks selected by each user i. The weight of each task r_j is equal to the set quality threshold Q_{r_j}, and represents the importance of the task to platform revenue. As in [15], the logarithm is used to represent the decreasing marginal returns of perceived quality. Additionally, a valuation function $\phi(i)$ is defined to represent the contribution value of user i. To sum up, we assume that $\phi(i)$ is a strictly monotonically increasing concave function related to q_i^l, defined as $\phi(i) = \sum_{i\in\widehat{W_{win}^l}} u_i^l \log\left(1 + \left|\Gamma_i^l\right| q_i^l\right)$. By substituting into Formula (15), the platform utility can be calculated as follows:

$$U_p = \sum_{i\in\widehat{W_{win}^l}} \left(\sum_{i\in\widehat{W_{win}^l}} u_i^l \log\left(1 + \left|\Gamma_i^l\right| q_i^l\right) \right) - \sum_{i\in\widehat{W_{win}^l}} p_i \tag{15}$$

The following section describes the simulation experiments and provides a comparative analysis of the mechanism.

4. Simulations and Evaluations

To assess the performance of the TB-HQ, we conducted numerous simulations and compared it with NMBIM [23], MCBS [17], and ABSee [15]. NMBIM and MCBS demonstrate excellent incentive effects in terms of participation levels and data quality, even under limited budget conditions. ABSee selects users based on both quality and cost, which maximizes the benefits of the platform. This approach provides a strong incentive for users to perform well. To ensure the experiment's fairness, this paper performs simulation experiments based on the same initial parameters. The experimental parameter list is shown in Table 2.

The following will be introduced in two parts. In Section 4.1, we simulate TB-HQ and evaluate the simulation results. In Section 4.2, we compare the simulation results of TB-HQ with the performance of other incentive mechanisms.

Table 2. Experimental parameter settings.

Symbol	Value	Description
N	[500, 1000]	Number of users
M	2000	Number of tasks
χ	[100, 200]	Task bonus
B	2×10^6	Platform budget
ζ	[0.3, 0.5]	Dependence factor
θ	20	Quality threshold
γ	200	Participation threshold

4.1. Mechanism Assessment

This subsection discusses the participation potential ϖ_i^l first, which represents the user's willingness to participate. The user will choose to participate in the task when this value exceeds the user participation threshold. The participation potential ϖ_i^l is related to the task bonus and its weight factor, as shown in Formula (4), where $\beta = 1 - \vartheta$. The relationship between the weight factor β, ϑ, task bonus χ_i^l, and participation potential ϖ_i^l was considered and is shown in Figure 3. The figure indicates that as χ_i^l increases while ϑ is constant, the user's participation potential ϖ_i^l increases, which is consistent with the discussion results of Theorem 1. Additionally, task bonuses χ_i^l play a positive role in motivating users to choose tasks.

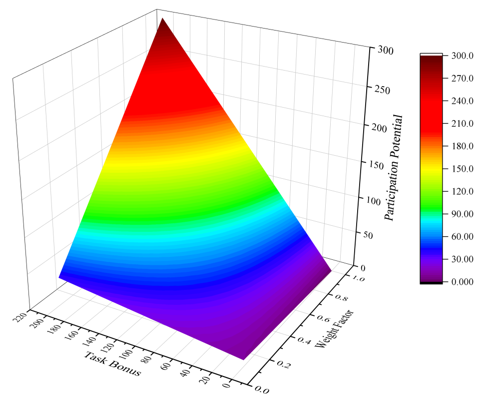


Figure 3. Effects of χ_i^l and ϑ on participation potential.

Next, we evaluate the algorithm for updating quality in the mechanism. We established 500 users and evenly distributed the initial quality q_i^0 in the range of 0 to 1. We then conducted multiple simulations of Algorithm 5 in the context of crowdsensing to demonstrate how the data quality was updated round by round, as illustrated in Figure 4. The horizontal axis represents the user ID, and the numerical axis represents the quality of data submitted by the corresponding user in the corresponding round. The purple, green, and yellow bar charts represent the data quality of 500 users after the 1st, 2nd, and 3rd updates, respectively. Figure 4 shows the quality of data submitted by users over time. It is evident from the figure that the quality of data submitted by users improves as the number of updates increases.

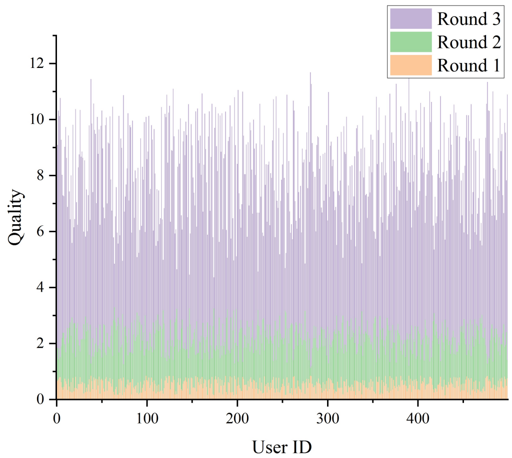


Figure 4. The relationship between the updated round and the data quality.

In Section 3.3, this paper sets a quality threshold for users. If the data quality submitted by the user is lower than the quality threshold, the user is a low-quality user, otherwise it is a high-quality user. According to Formulas (9) and (10), it can be seen that the avoidance utility of low-quality users is related to their data quality q_i^l and quality threshold θ. Therefore, according to formula 10, this paper obtains the avoidance utility value under the influence of quality thresholds θ and data quality q_i^l with different values, as shown in Figure 5. Figure 5 illustrates the correlation between the data quality q_i^l and the avoidance utility $\mathcal{R}(\Delta p_i^l)$ of low-quality users $i \in \widehat{W_{win}^L}$ across various quality thresholds θ. The user's avoidance utility decreases as the data quality increases under the same quality threshold. This is due to the positive correlation between the quality of the data submitted by the user and the amount of remuneration b_i^l received, as shown in Formula (8). When improving data quality leads to an increase in the remuneration b_i^l, the avoidance utility decreases. This phenomenon is in line with the proof of Theorem 4. Additionally, Figure 5 shows that the higher the quality threshold, the higher the rate of change of avoidance utility with quality. This shows that below the quality threshold set by the platform, avoidance utility is sensitive to changes in data quality, so that users with low quality can reduce avoidance utility by submitting higher quality data.

According to Formula (12), this paper obtains the user utility value of different values of quality threshold and data quality, as shown in Figure 6. Figure 6 illustrates the correlation between various quality thresholds θ, data quality q_i^l, and user utility Π_i^l. Figure 6a presents a three-dimensional graph of user utility at different quality thresholds and data quality levels. Figure 6b is a subset of Figure 6a and depicts the quality threshold. The trend of user utility changing with quality is shown for four different values. As can be seen from Figure 6, for a given quality threshold, the higher the quality, the higher the corresponding user utility, and the user utility shows two different growth trends as the data quality increases. This is because it can be seen from Formula (12) that high- and low-quality users, distinguished by quality thresholds, use different methods to calculate user utility. This phenomenon is consistent with the proof of Theorem 3. An obvious increase that changes from yellow to red can be observed in the surface of Figure 6a, which represents the corresponding quality threshold. If the data quality is below the threshold, the rate of change in user utility as quality increases is generally stable. Once the data quality meets the threshold requirement, user utility still increases with quality, but will eventually level off. Figure 6b provides a more intuitive representation. The figure shows quality thresholds for the four curves, indicated by vertical dotted lines of corresponding colors. Steep increases in user utility curves occur when quality growth exceeds the threshold, followed by a plateau.

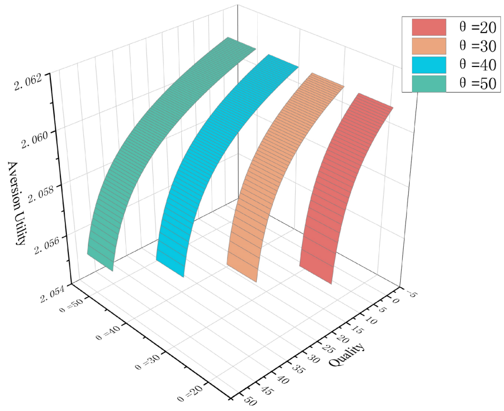
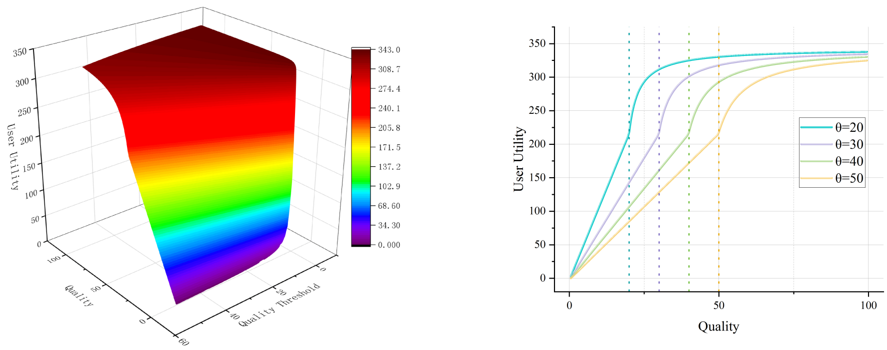


Figure 5. Effects of q and θ on avoidance utility.



(**a**) User utility changes with q and θ (**b**) User utility changes with q, θ=20, 30, 40, 50

Figure 6. Effects of q and θ on user utility.

4.2. Comparison with Other Mechanisms

In this subsection, the paper compares with NMBIM [23], MCBS [17] and ABSee [15] based on parameters such as the platform participation level, data quality, user utility, platform utility, and social welfare.

Figure 7 illustrates the incentive effect of four mechanisms in increasing user participation. The scatter clusters of four colors, distributed from top to bottom, represent the number of participations of 500 user samples under the influence of TB-HQ, NMBIM, MCBS, and ABSee. It is evident from the figure that TB-HQ has the highest number of user participations, followed by NMBIM, and finally MCBS and ABSee. TBIM in TB-HQ has pre-issued task bonuses compared to other mechanisms. This design will improve users' assessment of the value of task bonuses, and influence users' reference points for judging gains and losses. Users will not be able to keep their task bonuses if they do not participate in the tasks, and they will recognize this status as a loss. When comparing participating in tasks and not participating in tasks, users will choose the option of participating in tasks with higher utility.

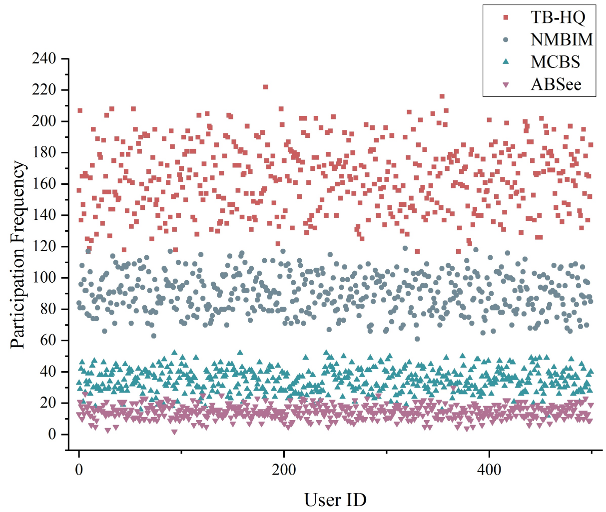


Figure 7. Comparison of participation frequency among various mechanisms.

Figure 8 compares the data quality of 500 users across three mechanisms. The width of the color block in the figure indicates the distribution of values, with wider color blocks representing areas with a larger distribution of values. In the figure, the quality threshold $\theta = 60$ is represented by the red dotted line. Figure 8 shows that, under the influence of TB-HQ, the majority of the user's data quality exceeds the quality threshold and the average value is 68.686. Conversely, most of the data quality under NMBIM falls within the range of 50 to 60, the average value is 51.766, and the data quality under the influence of TB-HQ is improved by 32.7% compared to the data quality under the influence of NMBIM. The other two mechanisms fall below the quality threshold. This is because HQWSM in TB-HQ sets an avoidance utility in combination with task bonuses, which is used to represent the disutility generated when users lose task bonuses due to low data quality. Users make decisions by evaluating the utility of high-quality and low-quality participation plans. Influenced by the avoidance utility, users will evaluate the utility of high-quality participation plans higher. HQWSM thus incentivizes users to improve data quality.

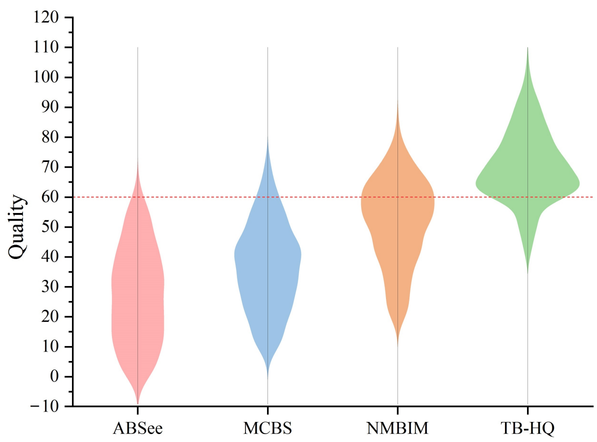


Figure 8. Comparison of data quality among various mechanisms.

Next, we selected 20 user samples at random to compare their utility, as shown in Figure 9. The numbers within the outer circle of the figure represent user IDs, and the four solid color blocks represent the utility of each user under the same budget for the four mechanisms: TB-HQ, NMBIM, MCBS, and ABSee. Figure 9 shows that the closed color block area for TB-HQ is the largest, followed by NMBIM and ABSee. The TB-HQ color block completely covers the color blocks for other mechanisms. Under the same budget, TB-HQ generally provides higher user utility compared to NMBIM and other mechanisms. Under the influence of TB-HQ, the average utility of 500 users is 185.987, which is 37.9% higher than the user utility under the influence of NMBIM.

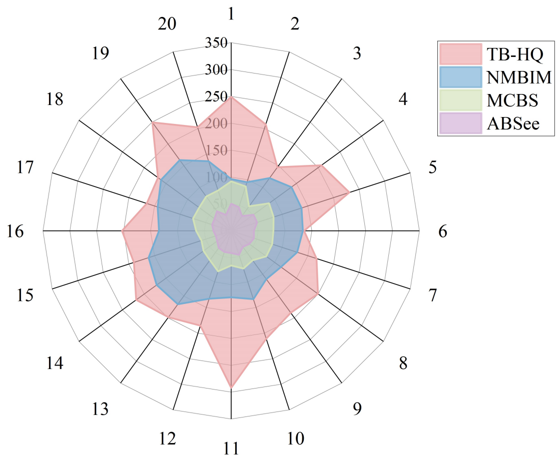


Figure 9. Comparison of partial user utility of each mechanism.

Finally, we adjusted the number of platform users and conducted multiple simulation experiments to compare the effects of the four mechanisms on improving platform utility. Figure 10 shows that TB-HQ has the highest platform utility, followed by NMBIM, MCBS, and ABSee. It is worth noting that TB-HQ has a significantly higher platform utility than MCBS and ABSee, and it also outperforms NMBIM. When the number of users is 500, the platform utility under the influence of TB-HQ is 77.3% higher than that of NMBIM. TB-HQ has been shown to be more effective in motivating users to increase their participation levels and improve their perceived data quality, resulting in a significant improvement in platform utility. The TBIM in TB-HQ provides incentives for participation levels, while the HQWSM provides incentives for improving data quality.

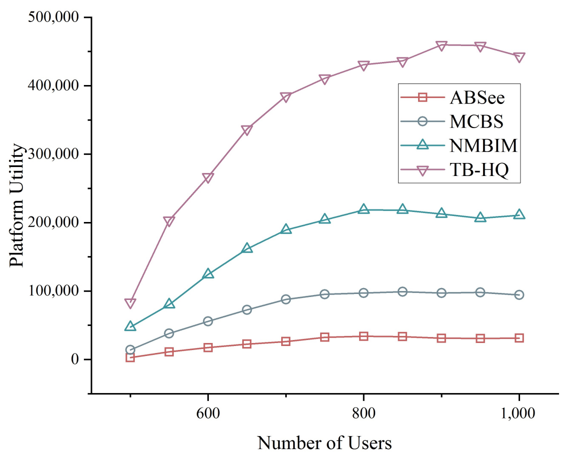


Figure 10. Comparison of platform utility among various mechanisms.

Figure 11 illustrates the impact of four mechanisms on social welfare. It is evident from the figure that MCBS and ABSee had a limited impact on social welfare after the number of users exceeded 750, while NMBIM did not significantly increase social welfare after the number of users reached 800. In contrast, TB-HQ resulted in significantly higher social welfare than the other three mechanisms, given the same budget and number of users. TB-HQ has significant advantages in improving social welfare. This is because it prompts users to participate in tasks multiple times, resulting in higher data quality while maintaining platform costs, thus achieving a better incentive effect.

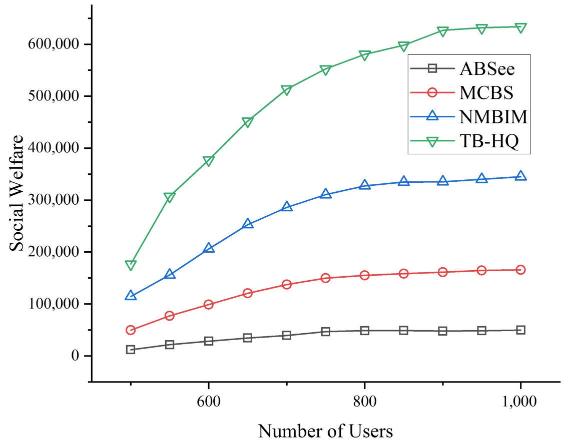


Figure 11. Comparison of social welfare among various mechanisms.

5. Conclusions

This paper mainly introduces the design and modeling of the incentive mechanism for participation level and data quality in crowdsensing. The main contributions are as follows:

- To address the problem of low user participation levels, we designed the task bonus-based incentive mechanism (TBIM). TBIM encourages users to increase their willingness to participate in tasks in order to avoid losing task bonuses by increasing users' valuation of task bonuses they have received.
- To address the problem of low data quality, we designed the high quality-driven winner screening mechanism (HQWSM). HQWSM takes advantage of users' unequal preferences for equal amounts of gains or losses, prompting users to improve data quality to avoid losses.
- The results of the simulation experiments showed that, under the action of TB-HQ, the user's data quality improved by 32.7%, and the platform utility increased by 77.3% compared to the comparison mechanism.

In addition, our methods still have shortcomings. In future work, we will consider user privacy protection issues in our methods, and increase users' trust in the platform by ensuring user privacy, thereby increasing users' enthusiasm for participation. Simultaneously, we will introduce additional constraint variables that align with real-life scenarios in the model. We will then evaluate the model's practical application in conjunction with small-scale real-time scenarios to comprehensively reflect the situation when users perform tasks.

Author Contributions: M.Z., W.Z. and J.L. designed the project and drafted the manuscript, as well as collected the data. Q.W. wrote the code and performed the analysis. All participated in finalizing the manuscript. All authors have read and agreed to the published version of the manuscript.

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Abbreviations

Variable	Description
$\mathcal{R}^l$	Task set published by the platform in round l
Γ_i^l	User i participation strategy in round l
W_u^l	User set in round l
$\widehat{W_w in}^H, \widehat{W_w in}^L$	Winner sets for high-quality domains and low-quality domains
B, χ_i^l	Total platform budget and task bonus
b_i^l, c_i^l	Bids and costs of User i in round l
δ_i^l, Ω_i^l	Propensity of User i towards the task set and the stickiness of User i towards task bonus
ϖ_i^l, γ_i^l	Participation potential and target threshold of User i
ψ_p^l, p_i^l	Platform revenue and user remuneration in round l
$q_i^l, \widehat{q_i^l}$	The user's total quality and single quality in round l
θ	Quality threshold specified by the platform
Φ_i^l, ℓ_i^l	User contribution value and converted bonus
λ, ε	The impact of user preferences on loss rewards

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