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Decision Analysis under Behavioral Economics—Incentive Mechanism for Improving Data Quality in Crowdsensing

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Abstract: Due to the profitability and selfishness of crowdfunding system users, under fixed budget conditions, there are problems, such as low task completion rate due to insufficient participants and low data quality. However, the existing incentive mechanisms are mainly based on traditional economics, which believes that whether users participate in tasks depends on whether the benefits of the task outweigh the costs. Behavioral economics shows that people judge the value of gains and losses according to a reference point. The weight given to losses is more important than the weight given to the same gains. Therefore, this article considers the impact of reference dependency and loss aversion on user decision-making and proposes a participant selection mechanism based on reference dependency (PSM-RD) and a quality assurance mechanism based on loss aversion (QAM-LA). PSM-RD uses reference points to influence user pricing and selects more participants based on relative value. QAM-LA pays additional rewards based on the data quality of participants and motivates them to improve data quality by reconstructing utility functions. The simulation results show that compared with the ABSee mechanism, data quality has improved by 17%, and the value of completed tasks has increased by at least 40%.

Keywords: mobile crowdsensing; task completion rate; data quality; reference dependence; loss aversion

MSC: 37M10

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1. Introduction

Mobile Crowdsensing (MCS) consists of three parts, the server platform, data requester, and data provider. The data requester requests data or services from the platform. The platform connects data requesters and data providers, receiving requests from data requesters and transforming them into tasks for publication to all data providers. At the same time, the platform is responsible for selecting participants, conducting quality checks on the data uploaded by data providers, and distributing rewards to data providers. The data provider is the participant in the task [1]. MCS is widely used in environmental monitoring [2,3], intelligent transportation [4,5], and other fields [6–8]. In MCS applications, data quality is a key factor in measuring the sensing level, and high-quality data to high-precision, wide-coverage, and low-redundancy data submitted within a specified time [9]. For example, people use vertical acceleration sensing information with data accuracy of cm/s^2 to draw a road smoothness map, which can find and improve road conditions in time [10]. When the user completes the sensing task, the devices' computing resources will be consumed [11–13]. These result in a low task completion rate, and participants are more reluctant to improve data quality.

Thus, incentive mechanisms, including non-monetary and monetary, are currently used to motivate users to participate and improve data quality [14]. The non-money incentive mechanism mainly uses reputation mechanism [15], virtual credit mechanism [16], etc., for incentives. Since there are many specific requirements for applying non-monetary mechanisms, the current incentive mechanisms are mainly monetary incentive, which pays the participant's sensing cost to improve the task completion rate [17] and submit high-quality data [18–22].

However, there are two problems. Firstly, the current mechanisms are mainly based on the cost–benefit model of traditional economic theory. Users will participate in sensing tasks as long as the benefits of completing the task outweigh the costs. In addition, the current mechanism assumes that when participants face equal losses and benefits, the absolute utility value is equal as long as the benefits of completing the task are equal. However, the reference dependence theory in behavioral economics [23] shows that the user's decision is affected by the relative value, that is, by the difference between revenue and the reference point [24,25]. When the reference point affects the user's decision, the external environment is the exogenous reference point, and the user's changes are the endogenous reference point [26,27]. Based on the two reference points, the difference in profit between a participant and other participants is the exogenous reference point, and the change in reward earned by the participant is the endogenous reference point. Otherwise, the loss aversion theory points out that when evaluating utility, if the benefit is above the reference point, it is regarded as a gain. Otherwise, it is viewed as a loss below the reference point [24]. Moreover, the evaluation value of the loss is more than the evaluation value of the gain [28]. In summary, current incentive mechanisms have theoretical defects in motivating data quality, resulting in higher theoretical data quality than the actual situation.

This paper introduces the reference dependence theory and loss aversion theory of behavioral economics to design an incentive mechanism to improve the task completion rate and promote the data quality in MCS. In summary, the main contributions of this paper are as follows:

- The paper proposes a participant selection mechanism based on reference dependency (PSM-RD). By setting the average pricing and average extra reward as the reference point, the relative value is used to reduce the user's pricing, increase the number of users who meet the selecting conditions within the platform budget, and thus improve the task completion rate.
- The paper proposes a quality assurance mechanism based on loss aversion(QAM-LA). According to the quality of the data submitted by the participant, an extra reward will be issued. The utility function is reconstructed using loss aversion theory, and the evaluation of negative utility is influenced by the extra reward, increasing the probability of participants submitting high-quality data.

The rest of the paper is organized as follows. Section 2 introduces the existing incentive mechanism and some studies in behavioral economics. Section 3 introduces a system model for MCS and the proposed system, mainly consisting of PSM-RD and QAM-LA. Section 4 verifies the effectiveness of the proposed mechanism through simulation experiments. Finally, in Section 5, we summarize our conclusions.

2. Related Work

This section summarizes the existing MCS incentive mechanisms and then introduces the reference dependence and loss aversion theories.

2.1. Mobile Crowdsensing Incentive Mechanism

Existing MCS incentive mechanisms are divided into non-monetary incentives [15,16,29–33] and monetary incentives [34–41]. Non-monetary incentives include based on entertainment games, based on services, and based on reputation. Incentives based on entertainment games and those based on services depend on a specific environment, while the quantitative standard of incentive mechanisms based on reputation cannot be unified. Thus, the non-monetary incentives are limited [42]. Monetary incentives typically use profits or bonuses to compensate for sensing costs and apply to various sensing scenarios. Often, monetary incentives are better at motivating participants to participate [43].

Guaranteeing the task completion rate is the basis for obtaining high-quality data [34,44,45]. To improve the task completion rate under budget constraints, Ref. [46] proposes a reverse auction-based mechanism combined with a geometric coverage model. Ref. [47] applies the Stackelberg game model to improve the task completion rate and data quality based on the principle of utility maximization. Ref. [48] considers the case where participants drop out randomly and determines the participant's payout in proportion to time, which improves the task completion rate and average participant utility. Ref. [49] introduces a mathematical model to characterize the data quality and maximize the collection of high-quality data while improving the task completion rate by optimizing the utility function.

The average quality of data is an essential measure of the sensing level. Ref. [39] proposes a mechanism considering participants' social networks to achieve long-term incentives to improve data quality. Ref. [50] proposed a mechanism based on reverse auction, recruiting participants who are more likely to submit high-quality data. Ref. [51] optimized the quality reward strategy based on the matching degree of tasks and participants, which improved the data quality and budget consumption rate. The reward distribution in [52] was determined by the weighted participant reputation, which guarantees the number and quality of users participating in the task. Ref. [51] solves the quality maximization problem by formalizing the reward payment and using the Lambert W function to obtain the optimal price under budget constraints. Ref. [53] maps participant rewards to reputation and rated reputation based on engagement and data accuracy to improve data quality. Ref. [54] selects the highest quality datasets based on 2D image features for maximally satisfying different quality requirements within the budget. Ref. [55] selects participants and assigned tasks according to the participant's sensing ability attribute value, and proposes a data quality self-estimation method to urge participants to improve data quality actively. Ref. [56] uses the deviation between reliable data and ground-truth values to quantify data quality and assigns rewards based on data quality to improve data quality under budget constraints.

However, the existing incentive mechanisms generally have the following problems. The mechanism of recruiting users through pricing does not consider the relative value formed by setting reference points, which will affect pricing. For example, in [46], the participant adjusts the bid based on the absolute percentage of the current bid rather than the relative value of the current bid and the participant's lowest bid. Ref. [48] did not consider the impact of falsely reported prices on bids when bidding. In [50], participants' bids, and the platform selects the winner based on prices, not considering other factors. In addition, participants with a high reputation in [52] received higher rewards. Otherwise, when calculating the utility, current incentive mechanisms did not consider that the impact of the same amount of loss is more significant than the same amount of gain on the participant's decision-making. Ref. [57] assumes that there is no other loss except the cost that the participant has paid after the task fails. In [48,50], the utility function value was zero when the participant did not complete the task. In order to solve the above problems and consider the differences between the scenarios, it is necessary to reconstruct the model and design a more effective incentive mechanism. Therefore, this paper introduces a reference dependence-based mechanism to influence participants' pricing and uses a loss aversion-based mechanism to promote participants to improve data quality.

2.2. Behavioral Economics

Reference dependence refers to the influence of other factors when an individual makes decisions, that is, reference points [24,25]. The reference point is a vital aspect distinguishing traditional and behavioral economics. It expresses the individual's expectation of the decision result, and the most recent choice determines the next reference point [24,25,58]. Usually, the utility function $v(\Delta x)$ is used to measure the deviation of the actual outcome of the decision from the expected outcome. When the actual decision result is better, $v(\Delta x) > 0$, otherwise $v(\Delta x) < 0$. Compared with the reference point, even if losses and gains are equal, the negative utility brought by losses is greater than the positive utility brought by gains, that is, loss aversion [23,59–62]. Figure 1 illustrates the difference between utility functions in traditional economics and behavioral economics.

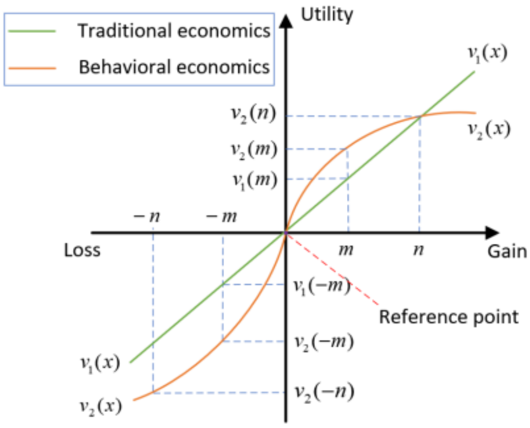

Figure 1. User utility function.

In Figure 1, quadrant I represent the utility curve at the time of gain, and the third quadrant represents the utility curve at the time of loss. It is known from Figure 1 that the utility curve in traditional economics $v_1(x)$ is a straight line with a constant slope, which represents the same amount of losses and gains with equal utility. That is, for any value of m, when $|-m| = |m|$, there is $|v_1(-m)| = |v_1(m)|$. However, the utility curve in behavioral economics $v_2(x)$ is divided into two parts. The slopes of the curves in quadrants I and III are different, and the curve in quadrant III is steeper. That is, the slope of the loss part is larger. Figure 1 shows that in the face of equal losses and gains, the negative utility brought by losses is greater than the positive utility brought by gains. Namely, when $|-m| = |m|$, there is $|v_1(-m)| > |v_1(m)|$.

To quantify loss aversion more accurately, [63] gives the loss aversion utility function under risk conditions, expressed as Formula (1).

$$v(x) = \begin{cases} (x-p_0)^{\alpha}, & x \geq p_0 \\ -\lambda(p_0-x)^{\beta}, & x < p_0 \end{cases} \tag{1}$$

where p_0 represents the reference point, α and β are risk attitude coefficients and $0 < \alpha$, $\beta < 1$, λ is the loss aversion coefficient and $\lambda > 1$.

In order to solve the two problems of low task completion rate and low data quality, reference dependence theory and loss aversion theory are introduced to design a more effective incentive mechanism.

3. Design and Analysis of PSM-RD and QAM-LA

Section 3.1 introduces the system model. Sections 3.2 and 3.3 detail the design and principle of PSM-RD and QAM-LA, respectively. Finally, we illustrate PSM-RD using examples.

3.1. System Model

This section will further illustrate the physical model in combination with the physical background and construct the logical model of the incentive mechanism.

3.1.1. Physical Model

MCS consists of three parts, the server platform, data requester, and data provider. The data requester informs the platform of task requests and related information. The platform publishes these tasks to users, collects information, such as user pricing, selects participants under budget constraints, and pays rewards after the participants submit the data. At the same time, the platform can use incentive mechanisms to achieve specific goals, such as obtaining higher data quality through incentive mechanisms. The sensing process of MCS is generally divided into six sub-processes, and the corresponding process in specific application scenarios is shown in Figure 2.

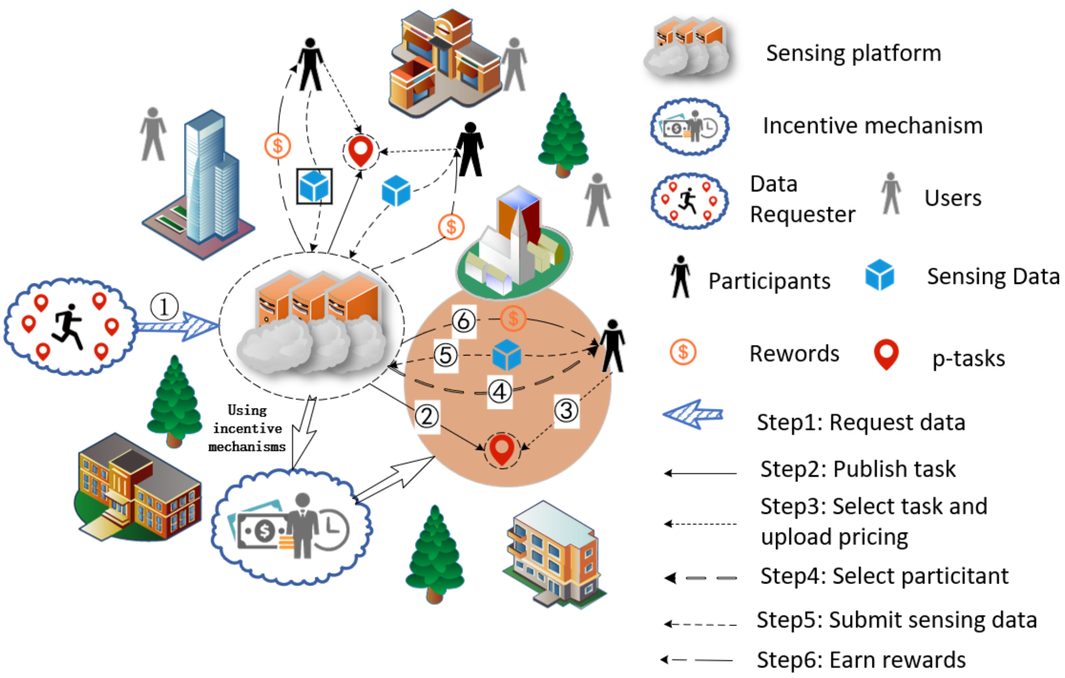

Figure 2. Physical model.

The specific physical process is as follows.

(1) Proposing task requirements. The task initiator submits task requirements to the platform, including data requirements, task budget, acceptable delay, task value, and other attributes. Each task is indivisible.

(2) Publishing task. After receiving the request, the platform publishes the r^{th} round of task sets $\mathbb{T} = \{t_1, t_2, \ldots, t_m\}$ and related attributes to the user sets $\mathbb{P} = \{p_1, p_2, \ldots, p_n\}$ of size $n \in N^+$, where $m \in N^+$ and $m \geq 2$.

(3) Selecting tasks and uploading pricing. The user p_i uploads pricing 2-tuple $Price_i^r = \{T_i^r, b_i^r\}$ to the platform according to the attributes of the task and their abilities, where $T_i^r = \{t_{i,1}, t_{i,2}, \ldots, t_{i,m}\}$ is the task sets priced by p_i, $t_{i,m}$ is the m^{th} task priced by p_i, and b_i^r is the total pricing corresponding to T_i^r. Due to the possible correlation between multiple tasks, the total cost of a task set is not necessarily equal to the sum of the costs of each task. Therefore, this article uses the total pricing b_i^r for the task set T_i^r.

(4) Selecting the participant. The platform selects the users according to PSM-RD and obtains participant sets $W^r = \{w_1, w_2, \ldots, w_s\}$ of size $s \in N^+$, where $0 \leq s < n$ and $W^r \subseteq \mathbb{P}$. For any $p_i \notin W^r$, it needs to reduce the pricing to be selected by the platform.

(5) Completing tasks and submitting sensing data. After the participant p_i completes the sensing task sets T_i^r, the collected data are processed by the platform and fed back to the task initiator.

(6) Paying the reward. After evaluating the data quality of p_i, the platform pays p_i the corresponding extra reward $\mathcal{B}_i^k$ according to QAM-LA. Users who fail to obtain $\mathcal{B}_i^k$ must continue participating in the task and submit high-quality data to obtain the extra reward temporarily frozen $\mathcal{F}_i^r$.

3.1.2. Logical Model

The incentive mechanism mainly includes PSM-RD and QAM-LA, which mainly involve platform and participant sets. The design of the logical framework for PSM-RD and QAM-LA is shown in Figure 3, where the PSM-RD acts on all users to change their pricing through reference points, the platform selects participants through the relative value ratio, selecting more participants, and the QAM-LA mechanism incentivizes participants through loss aversion, improving their data quality.

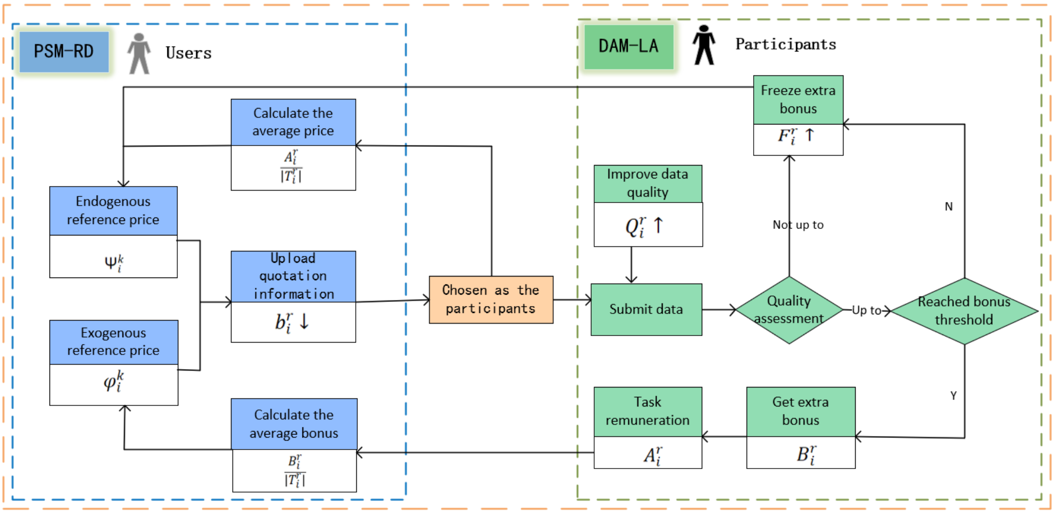

Figure 3. Design of logical framework for PSM-RD and QAM-LA.

Definition 1. *(Average pricing ψ_i^k). If p_i was selected as a participant in the most recent round (assuming that the k^{th} round and $k < r$), its pricing tuples are $Price_i^r = \{T_i^r, b_i^r\}$ and submits high-quality data this round, then the average pricing of p_i for a single task in the k^{th} round $\psi_i^k = \frac{b_i^k}{|T_i^k|}$. Otherwise, ψ_i^k does not exist. The definition of ψ_i^k is shown in Formula (2).*

$$\psi_i^k = \begin{cases} +\infty, & p_i \notin W^r \text{ and } 1 \le k < r \\ \frac{b_i^k}{|T_i^k|}, & p_i \in W^r \text{ and } 1 \le k < r \end{cases} \tag{2}$$

Definition 2. *(Average extra reward φ_i^k). If p_i was selected as participant in k^{th} round and obtained extra reward $\mathcal{B}_i^k$, then the average extra reward in the k^{th} round is $\varphi_i^k = \frac{\mathcal{B}_i^k}{|T_i^k|}$. Otherwise, φ_i^k does not exist. The definition of φ_i^k is shown in the Formula (3).*

$$\varphi_i^k = \begin{cases} -\infty, & p_i \notin W^r \text{ and } 1 \le k < r \\ \frac{\mathcal{B}_i^k}{|T_i^k|}, & p_i \in W^r \text{ and } 1 \le k < r \end{cases} \tag{3}$$

The goal of the PSM-RD is to improve the task completion rate. Combined with the relevant research on reference points, when p_i participates in bidding, the average pricing ψ_i^k is the exogenous reference point, and the average extra reward φ_i^k is the endogenous reference point, both of which affect the user's pricing b_i^r. After p_i submits the pricing, the platform selects the participant w_s to complete the task by the ratio of user's pricing to task's value. Users who fail to become participants must decrease the pricing b_i^{r+1} to meet the selecting criteria of the platform, then they can complete the task and receive payment.

The goal of the QAM-LA is to improve the data quality. After the participant submits the data, the platform evaluates the level of data quality $\mathcal{K}_i^r$ according to the average level $\mathcal{H}^r$ of the data quality $\mathcal{Q}_i^r$, where Sdq, Mdq, and Idq represent good, general, and low data quality, and the equation will be discussed in Section 3.1.1, respectively. The platform pays the corresponding payment according to $\mathcal{K}_i^r$. If participants submit high-quality data, they will also receive an extra reward $\mathcal{B}_i^r$, and the total payment $\mathcal{A}_i^r$ includes the task payment and extra reward. Otherwise, the platform will temporarily withhold its extra reward $\mathcal{B}_i^r$. if participants lose extra rewards, the total payment is less than the sensing cost. To avoid losses, participants must continue to improve data quality $\mathcal{Q}_i^{r+1}$ for extra rewards.

To motivate participants to continue to participate in sensing tasks and improve the data quality $\mathcal{Q}_i^{r+1}$, when participants submit high-quality data, i.e., $\mathcal{K}_i^r = Sdq$, the platform pays all its payment and extra reward. Otherwise, the platform temporarily freezes its extra reward $\mathcal{B}_i^r$. When the accumulated extra frozen rewards $\mathcal{F}_i^{r+f}$ reaches a specific value $\eth_i$, and high-quality data are submitted in this round, the platform will issue all extra rewards temporarily frozen.

Definition 3. *(Sensitivity factor $\int_i^r$). Assuming that participant p_i's accumulated frozen extra rewards in multiple rounds is $\mathcal{F}_i^r$, and the unfreezing threshold for extra reward is $\eth_i$, then $\mathcal{F}_i^r = \sum_{p_i \in W^r \text{ and } \mathcal{K}_i^r \neq Sdq} \mathcal{B}_i^r$ and $\eth_i = \frac{1-\theta}{\theta} b_i^r$. The definition of $\int_i^r$ is shown in the Formula (4).*

$$\int_i^r = \frac{\mathcal{F}_i^r}{\eth_i} = \frac{\sum_{p_i \in W^r \text{ and } \mathcal{K}_i^r \neq Sdq} \mathcal{B}_i^r}{\frac{1-\theta}{\theta} b_i^r} \tag{4}$$

where W^r is the sets of participants of the r^{th} round of sensing tasks, K_i^r is the level of data quality, Sdq represents the level of good data quality, $\mathcal{B}_i^r$ is the extra reward of the r^{th} round of w_i, b_i^r is the total pricing of p_i to the task set T_i^r in the r^{th} round, and θ is the budget allocation factor which the meaning is given in Section 3.2.1.

If the extra reward $\mathcal{B}_i^r$ is lost, the gain after completing the sensing task is less than zero. The sensitivity factor measures the impact of $\mathcal{B}_i^r$ on the participant's utility u_i^r. To avoid the sensing cost, the participant must improve the data quality $\mathcal{Q}_i^{r+1}$ to increase the participant's total utility u_i^r. When the participant participates in pricing, the average pricing ψ_i^k is the exogenous reference point, and the extra reward φ_i^k is the endogenous reference point. Under the influence of the exogenous reference point and the endogenous reference point, the participant updates the pricing b_i^{r+1} to meet the selection criteria of the platform. Table 1 lists some symbols commonly used in this paper and their meanings.

Table 1. Common symbols and meanings.

Variable	Description
T_i^r	In r^{th} round, the sets of tasks that p_i participates in pricing
b_i^r	Total pricing of p_i to T_i^r
V_i^r	Total value of all tasks in T_i^r
v_i	The value of completing a single task t_i
$\mathcal{E}_i^r$	Cost-benefit conversion factor for p_i
C_i^r	The sensing cost of the p_i to complete the T_i^r
ξ_i^r	Pricing for unit value
W^r	The sets of participants of the r^{th} round of sensing tasks
$\mathcal{A}_i^r$	The total payment of w_i round r
$\mathcal{B}_i^r$	w_i extra reward for round r
$\mathcal{F}_i^r$	Accumulated frozen extra reward at round r
$\eth_i$	unfreezing threshold for extra rewards $\mathcal{F}_i^r$
f	The number of rounds for unfreezing the current $\mathcal{F}_i^r$
d	The total number of rounds for submitting high-quality data
u_i^r	The total utility of the r^{th} round of w_i
Q_i^r	The data quality of the r^{th} round of w_i
U^r	The total utility of the platform after round r

3.2. Participant Selection Mechanism Based on Reference Dependence

According to the physical model in Section 3.1.1, assuming that the sensing radius of the r^{th} round of p_i is d_i^r, and the distance between the user and the task $t_k \in T_i^r$ is $dist_{ik}^r$. The user can select and complete the task when $dist_{ik}^r < d_i^r$. When the user submits pricing, PSM-RD influences the user's pricing through the reference point.

3.2.1. Collecting User Pricing

Assuming that the total budget of the platform is G, and $\theta * G$ is used as the task payment $\mathcal{A}_i^r$ and $(1-\theta) * G$ is used as the extra reward $\mathcal{B}_i^r$, where θ is the budget allocation factor. At the same time, $\mathcal{A}_i^r \geq \mathcal{B}_i^r$ is required.

If p_i participates in the task sets in the r^{th} round $(r \geq 2)$ is T_i^r, and is selected as the participant in the k^{th} round, the average pricing and average extra reward are ψ_i^k and φ_i^k, respectively. From $\mathcal{A}_i^r \geq \mathcal{B}_i^r$, it is known that $\theta \geq 0.5$, then $\psi_i^r \geq \varphi_i^r$. As described in the reference dependency theory of behavioral economics introduced in the introduction, participants' behavior is affected by reference points (including endogenous reference points and exogenous reference points). Therefore, combining Definitions 1 and 2, the exogenous reference factor λ and the endogenous reference factor γ are used to represent the degree to which p_i is affected by ψ_i^k and φ_i^k, then its pricing $\hat{b}_i^r = \lambda \frac{b_i^k}{|T_i^k|} + \gamma \frac{\mathcal{B}_i^k}{|T_i^k|} = \lambda \psi_i^k + \gamma \varphi_i^k$ for a single task in the r^{th} round, where $0 < \lambda < 1$, $0 < \gamma < 1$ and $\lambda + \gamma = 1$. If p_i has not participated in any previous rounds, it makes pricing based on sensing cost. Therefore, the pricing of p_i in the r^{th} round is expressed as the Formula (5).

$$b_i^r = \begin{cases} \mathcal{E}_i^r * C_i^r, & (p_i \notin W^r \text{ and } r \geq 2) \text{ or } r = 1 \\ \left(\lambda \psi_i^k + \gamma \varphi_i^k\right) * |T_i^r|, & p_i \in W^r \text{ and } r \geq 2 \end{cases} \tag{5}$$

It can be known from Formula (5) that users who have become participants are affected by both the average pricing ψ_i^k and the average extra reward φ_i^k. For any $p_i \in W^k$, a certain task payment will be obtained after completing the task, and the payment will affect the pricing. That is, ψ_i^k will affect p_i's pricing b_i^r. The influence of λ on b_i^r will be explored in Theorem 1 below.

Theorem 1. *For any user $p_i \in \mathbb{P}$,when the value of λ increases,b_i^r increases. That is,$b_i^r \propto \lambda$.*

Proof of Theorem 1. Assuming that $\exists \lambda_1, \lambda_2$, and $0 < \lambda_1 < \lambda_2 < 1$, then $b_{i_1}^r - b_{i_2}^r = \left(\lambda_1 \psi_i^k + \gamma_1 \varphi_i^k\right) * |T_i^r| - \left(\lambda_2 \psi_i^k + \gamma_2 \varphi_i^k\right) * |T_i^r|$. From $\lambda + \gamma = 1$, there is $b_{i_1}^r - b_{i_2}^r = \left(\lambda_1 \psi_i^k + (1-\lambda_1)\varphi_i^k\right) * |T_i^r| - \left(\lambda_2 \psi_i^k + (1-\lambda_2)\varphi_i^k\right) * |T_i^r|$. After simplification, we obtain $b_{i_1}^r - b_{i_2}^r = |T_i^r| * \left[\left(\psi_i^k - \varphi_i^k\right)(\lambda_1 - \lambda_2)\right]$.

Because there is $\varphi_i^k \leq \psi_i^k$, there is $\psi_i^k - \varphi_i^k \geq 0$. Furthermore, because there is $\lambda_1 < \lambda_2$, then $\lambda_1 - \lambda_2 < 0$, we can obtain $b_{i_1}^r - b_{i_2}^r < 0$. That is, the larger the λ, the greater the impact of the average pricing on the participant's pricing. As the mechanism ensures that the average pricing is always higher than the average extra rewards. Therefore, the larger the λ, the greater the impact of the average pricing on the pricing in this round, that is, the higher the pricing. Then Theorem 1 is proved. □

It is known from Theorem 1 that λ and b_i^r are positively correlated. With the increase in λ, the weight of the influence of the average pricing on b_i^r increases. When reference dependence is not considered, the user's pricing b_i^r is only related to sensing cost C_i^r. In PSM-RD, the user's pricing b_i^{r+1} is influenced by the reference point. The following will explore the trend of user pricing after applying PSM-RD through Theorem 2.

Theorem 2. *For the same task sets $T \subseteq \mathbb{T}$, the pricing of p_i is $\tilde{b_i^r}$ when the reference dependence is not considered, and the pricing of p_i in PSM-RD is b_i^r, then $b_i^r \leq \tilde{b_i^r}$.*

Proof of Theorem 2. A. When $r = 1$, because there is no average pricing and average extra reward in the previous round, then there is no reference point, so $b_i^1 = \tilde{b_i^1}$;

B. When $r \geq 2$, there is $\tilde{b_i^r} = \widetilde{b_i^{r-1}} = \ldots = \tilde{b_i^1}$,if reference dependence is not considered. In PSM-RD, it can be known from Formula (5) that $b_i^r = \left(\lambda * \psi_i^k + \gamma * \varphi_i^k\right) * |T_i^r|$.

Because $T_i^k = T_i^r$, thus $b_i^r = \lambda\frac{b_i^k}{|T_i^k|} + \gamma\frac{\mathcal{B}_i^k}{|T_i^k|}$. It can be known from Theorem 1 that $\varphi_i^k \le \psi_i^k$, then $\varphi_i^k * \left|T_i^k\right| \le \psi_i^k * \left|T_i^k\right|$, so $\mathcal{B}_i^k \le b_i^k$. Furthermore, because $0 < \lambda,\gamma < 1$ and $\lambda + \gamma = 1$, we can obtain $\gamma\psi_i^k \le \gamma b_i^k$. From $b_i^r = \lambda b_i^k + \gamma\mathcal{B}_i^k \le \lambda b_i^k + \gamma b_i^k = b_i^k \le \ldots \le b_i^1 = \tilde{b}_i^1 = \tilde{b}_i^r$,there is $b_i^r \le \tilde{b}_i^r (r \ge 2)$. Combining A and B, we can see that $b_i^r \le \tilde{b}_i^r$. Theorem 2 is proved. □

It is known from Theorem 2 that the user's pricing b_i^r after applying PSM-RD is lower, It means that under the influence of the reference point, PSM-RD reduces the user's pricing. When the platform budget is fixed, the user decreases the pricing, the platform can select more participants from the user sets. The number of sensing tasks completed will increase accordingly.

3.2.2. Selecting Participants

After the user submits the pricing, the platform selects the participants. Because each user participates in a different number of tasks and the sensing cost of completing the sensing tasks is not equal, the user's pricing is also different. Therefore, in the criteria for selecting the participant, not only the pricing b_i^r of the task sets T_i^r, but also the value V_i^r of the task sets should be considered, and $\xi_i^r = \frac{b_i^r}{V_i^r}$. When selecting the participant, the user satisfied $\xi_i^r = 0$ is eliminated first. Then, the user whose value of ξ_i^r is smaller and $\xi_i^r < 1$ are selected in order from small to large. When $\sum\limits_{p_i \in W^r} \frac{b_i^r}{V_i^r} > 1$ stop selecting participants.

According to the participant selection criteria, for task sets $T_i^r \subseteq \mathbb{T}$, assuming that the number of participants without considering the reference dependence is $\tilde{\mathcal{S}}$, and there is the j^{th} participant p_j that satisfies $\sum\limits_{i=1,p_i \in W^r}^{j} \frac{\tilde{b}_i^r}{\tilde{V}_i^r} = \sum\limits_{i=1,p_i \in W^r}^{j} \tilde{\xi}_i^r > 1$ and $\sum\limits_{i=1,p_i \in W^r}^{j-1} \frac{\tilde{b}_i^r}{\tilde{V}_i^r} = \sum\limits_{i=1,p_i \in W^r}^{j} \tilde{\xi}_i^r \le 1$. From the above participant selection criteria, it is known that $\tilde{\mathcal{S}} = j - 1$.

Under the PSM-RD mechanism, assuming that the number of participants is S, it can be known from Theorem 2 that $b_i^r \le \tilde{b}_i^r$. For the same task sets $T_i^r \subseteq \mathbb{T}$,so $V_i^r = \tilde{V}_i^r$, then $\frac{b_i^r}{V_i^r} \le \frac{\tilde{b}_i^r}{\tilde{V}_i^r}$. Therefore, $\sum\limits_{i=1,p_i \in W^r}^{j-1} \frac{b_i^r}{V_i^r} \le \sum\limits_{i=1,p_i \in W^r}^{j-1} \frac{\tilde{b}_i^r}{\tilde{V}_i^r} \le 1$, there is at least the j^{th} participant p_j that satisfies $\sum\limits_{i=1,p_i \in W^r}^{j} \frac{b_i^r}{V_i^r} \le 1$. Furthermore, p_j is also the participant at this time, then $\mathcal{S} = j > j - 1$, thus $\mathcal{S} \ge \tilde{\mathcal{S}}$. Therefore, under the PSM-RD mechanism, more participants meet the participant selecting criteria, and the number of participants completing the task increases. Since each participant will complete at least one task, thus the number of tasks being completed increases, and then the task completion rate increases.

3.3. Data Quality Assurance Mechanism Based on Loss Aversion

When the task completion rate is improved and the amount of data collected by the platform is sufficient, the frequency of obtaining high-quality and low-quality data will increase. To solve the problem of low-quality data submitted by the participants, this section introduces the loss aversion theory of behavioral economics and designs QAM-LA based on Section 3.2.

3.3.1. Evaluation of the Data Quality

According to the formula of the quality [26] , Q_i^r is defined as the data quality of the task sets T_i^r completed by the participant w_i, denoted as Formula (6).

$$Q_i^r = \chi_i^r * \log(1 + \mathcal{J}_i^r) \tag{6}$$

where χ_i^r is the weight of T_i^r, and $\mathcal{J}_i^r$ is the average quality of T_i^rcompleted by w_i, denoted as Formula (7).

$$\mathcal{J}_i^r = \frac{1}{|T_i^r|} \sum_{t_k \in T_i^r} \delta_{ik}^r \tag{7}$$

where δ_{ik}^r is the data quality of w_i completing a certain task t_k. Assuming that $Q_{\max}^r$ and $Q_{\min}^r$ denote the maximum and minimum data quality, respectively, then the range of Q_i^r is expressed as Formula (8).

$$\mathcal{R}^r = Q_{\max}^r - Q_{\min}^r \tag{8}$$

Assuming that the average quality of the data submitted by the participants is $\mathcal{H}^r$, denoted as Formula (9).

$$\mathcal{H}^r = \frac{\sum_{p_i \in W^r} Q_i^r}{|W^r|} = \frac{\sum_{p_i \in W^r} \chi_i \log\left(1 + \frac{1}{|T_i|} \sum_{t_k \in T_i} \delta_{ik}\right)}{|W^r|} \tag{9}$$

When $Q_i^r > \mathcal{H}^r$, there is $\mathcal{K}_i^r = Sdq$. When $Q_i^r < \mathcal{H}^r$, assuming that the degree of deviation between Q_i^r and $\mathcal{H}^r$ is $\mathcal{D}_i^r = |Q_i^r - \mathcal{H}^r|$, denoted as Formula (10).

$$\mathcal{D}_i^r = \left| Q_i^r - \frac{\sum_{p_i \in W^r} Q_i^r}{|W^r|} \right| \tag{10}$$

Furthermore, the maximum value of $\mathcal{D}_i^r$ is $\mathcal{D}_{max}^r$. Assuming that the quality threshold interval of platform is $\left(\mathcal{H}^r - \frac{\mathcal{D}_{\max}^r}{3}, \mathcal{H}^r\right]$, then K_i^r is denoted as Formula (11).

$$\mathcal{K}_i^r = \begin{cases} Sdq, & Q_i^r \in (\mathcal{H}^r, +\infty) \\ Mdq, & Q_i^r \in \left(\mathcal{H}^r - \frac{\mathcal{D}_{\max}^r}{3}, \mathcal{H}^r\right] \\ Idq, & Q_i^r \in \left(-\infty, \mathcal{H}^r - \frac{\mathcal{D}_{\max}^r}{3}\right] \end{cases} \tag{11}$$

3.3.2. Calculating Payment

After the participant submits data, the platform will pay extra rewards according to $\mathcal{K}_i^r$. For any participant $w_i \in W^r$, when $\mathcal{K}_i^r = Sdq$, its extra reward is $\mathcal{B}_i^r = \frac{1-\theta}{\theta} b_i^r$, where θ represents the proportion factor of the budget for selecting the winners to the platform budget, and the extra reward is issued to w_i at one time. When $\mathcal{K}_i^r = Mdq$ or $\mathcal{K}_i^r = Idq$, the platform will temporarily freeze its extra rewards. Only when w_i continues to participate in the sensing task, the accumulated extra reward reach $\frac{1-\theta}{\theta} * b_i^r$, and the current round submits high-quality data, the platform will issue all the extra rewards temporarily frozen. Taking into account the sensing cost and the platform budget constraint, when $\mathcal{K}_i^r = Mdq$, its extra reward is $\mathcal{B}_i^r = \frac{2(1-\theta)}{3\theta} b_i^r$; when $\mathcal{K}_i^r = Idq$, its extra reward is $\mathcal{B}_i^r = \frac{1-\theta}{3\theta} b_i^r$. Therefore, $\mathcal{B}_i^r$ is expressed as the Formula (12).

$$\mathcal{B}_i^r = \begin{cases} \dfrac{1-\theta}{\theta} b_i^r, & \mathcal{K}_i^r = Sdq \\ \dfrac{2(1-\theta)}{3\theta} b_i^r, & \mathcal{K}_i^r = Mdq \\ \dfrac{1-\theta}{3\theta} b_i^r, & \mathcal{K}_i^r = Idq \end{cases} \tag{12}$$

Combined with Formula (12), assuming that the total payment for any participant w_i is $\mathcal{A}_i^r$. When $\mathcal{K}_i^r = Sdq$, it means that w_i submits high-quality data in this round, then $\mathcal{B}_i^r = \frac{1-\theta}{\theta} b_i^r$. If $\mathcal{F}_i^r = \eth_i$, then $\mathcal{F}_i^r$ can be unfrozen, thus $\mathcal{A}_i^r = \frac{1-\theta}{\theta} b_i^r + b_i^r + \mathcal{F}_i^r = \frac{b_i^r}{\theta} + \mathcal{F}_i^r$. If $\mathcal{F}_i^r < \eth_i$, then $\mathcal{F}_i^r$ cannot be unfrozen, thus $\mathcal{A}_i^r = \frac{b_i^r}{\theta}$. When $\mathcal{K}_i^r = Mdq$ or $\mathcal{K}_i^r = Idq$, it means that w_i did not submit high-quality data in this round, and $\mathcal{B}_i^r$ can be obtained, but both $\mathcal{B}_i^r$ and $\mathcal{F}_i$ are temporarily frozen by the platform, thus $\mathcal{A}_i^r = b_i^r$. In summary, $\mathcal{A}_i^r$ is expressed as the Formula (13).

$$\mathcal{A}_i^r = \begin{cases} \frac{b_i^r}{\theta} + \mathcal{F}_i^r, & \mathcal{K}_i^r = Sdq \ and \ \mathcal{F}_i^r = \eth_i \\ \frac{b_i^r}{\theta}, & \mathcal{K}_i^r = Sdq \ and \ \mathcal{F}_i^r < \eth_i \\ b_i^r, & \mathcal{K}_i^r = Mdq \ or \ \mathcal{K}_i^r = Idq \end{cases} \quad (13)$$

3.3.3. Utility Analysis

It is known from Section 3.3.2 that the maximum benefit of any w_i is $\mathcal{A}_{max}^r = b_i^r + \max(\mathcal{B}_i^r) + \eth_i$. If w_i does not submit high-quality data in this round, its total payment loss is $\mathcal{L}_i^r = \mathcal{A}_{max}^r - \mathcal{A}_i^r$, and it is defined as Formula (14).

$$\mathcal{L}_i^r = b_i^r + \max(\mathcal{B}_i^r) + \eth_i - \mathcal{A}_i^r \quad (14)$$

If w_i fails to obtain extra rewards because of not submitting high-quality data, the total payment obtained in this round is only close to the sensing cost C_i^r, the utility generated by the total extra reward loss value is negative. To sum up, for any participant $w_i \in W^r$, its utility u_i^r includes the positive utility brought by $\mathcal{A}_i^r$ and the negative utility $\mathcal{N}_i^r$ brought by $\mathcal{L}_i^r$, which is expressed as Formula (15).

$$u_i^r = \begin{cases} \mathcal{A}_i^r - C_i^r, & p_i \in W^r and Q_i^r \in (\mathcal{H}^r, +\infty) \\ \mathcal{A}_i^r - C_i^r + \mathcal{N}_i^r, & p_i \notin W^r or Q_i^r \notin (\mathcal{H}^r, +\infty) \end{cases} \quad (15)$$

where $\mathcal{N}_i^r = (-\lambda) * \left(\mathcal{A}_{max}^r - \mathcal{A}_i^r\right)^\beta$, and it is expressed as Formula (16).

$$\mathcal{N}_i^r = (-\lambda) * [b_i^r + max(\mathcal{B}_i^r) + \eth_i - \mathcal{A}_i^r]^\beta \quad (16)$$

From Formula (14), it is known that for any w_i,$\mathcal{L}_i^r \geq 0$. When $\lambda > 0$, there is $(-\lambda) * \mathcal{L}_i^r \leq 0$, then $(-\lambda) * \left(\mathcal{A}_{max}^r - \mathcal{A}_i^r\right)^\beta = (-\lambda) * \left[b_i^r + \max(\mathcal{B}_i^r) + \eth_i - \mathcal{A}_i^r\right]^\beta \leq 0$, thus $\mathcal{N}_i^r \leq 0$. If the user is not selected as the participant, that is, when $p_i \notin W^r$, $\mathcal{A}_i^r = b_i^r = 0$, then $u_i^r = 0$.

It is known from Definition 3 that when the value of $\int_i^r$ is closer to 1, it indicates that the accumulated frozen extra rewards are closer to the unfreezing threshold for extra rewards $\eth_i$. The negative utility of the participant w_i is more significant if the extra rewards temporarily frozen are lost. Therefore, when the value of $\int_i^r$ is more significant, the probability of the participant unfreezing the accumulated frozen extra reward is higher, and the probability of improving the data quality in the next round is more increased.

Assuming Q_i^r and Q_i^{r+1} denote the data quality of the participant in the r^{th} and $(r+1)^{th}$ rounds, respectively. When $\mathcal{K}_i^r \neq Sdq$, Q_i^{r+1} is simultaneously affected by Q_i^r and $\int_i^r$. When $\mathcal{K}_i^r = Sdq$ or $p_i \notin W^r$,Q_i^{r+1} is calculated according to Formula (6). Therefore, Q_i^{r+1} is expressed as the Formula (17).

$$Q_i^{r+1} = \begin{cases} \left(1 + \int_i^r\right) * Q_i^r, & \mathcal{K}_i^r \neq Sdq \\ \chi_i^r * \log\left(1 + \mathcal{J}_i^r\right), & \mathcal{K}_i^r = Sdq \end{cases} \quad (17)$$

Combining Equations (15) and (17), it is known that the participant's total utility u_i^r consists of positive and negative utility. Furthermore, Q_i^r determines the quality, which corresponds to different payments and extra rewards, and affects the total utility. Therefore, Theorem 3 will illustrate the relationship between Q_i^r, $\mathcal{N}_i^r$ and u_i^r.

Theorem 3. *For any w_i,the higher the data quality Q_i^r, the higher $\mathcal{N}_i^r$ and the higher u_i^r. That is, $Q_i^r \propto \mathcal{N}_i^r$ and $Q_i^r \propto u_i^r$.*

Proof of Theorem 3. Assuming that $C_{i_1}^r = C_{i_2}^r$ and $b_{i_1}^r = b_{i_2}^r$, there is $Q_{i_1}^{r+1} > Q_{i_2}^{r+1}$, satisfies $\mathcal{F}_{i_1}^r = \mathcal{F}_{i_2}^r$ and $\mathcal{K}_{i_1}^r \geq \mathcal{K}_{i_2}^r$, then we know from Formula (13) that $\mathcal{A}_{i_1}^r \geq \mathcal{A}_{i_2}^r > 0$.

Because $\mathcal{L}_i^r = b_i^r + max(\mathcal{B}_i^r) + \eth_i - \mathcal{A}_i^r$ and $max(\mathcal{B}_i^r) = \eth_i = \frac{1-\theta}{\theta} b_i^r$, thus $\mathcal{L}_{i_1}^r \leq \mathcal{L}_{i_2}^r$. Combined with Formula (17), we know $\mathcal{N}_{i_1}^r \geq \mathcal{N}_{i_2}^r$. When $C_{i_1}^r = C_{i_2}^r$, because of $\mathcal{A}_{i_1}^r \geq \mathcal{A}_{i_2}^r$ and $\mathcal{N}_{i_1}^r \leq \mathcal{N}_{i_2}^r \leq 0$, it is known from Formula (16) that $u_{i_1}^r \geq u_{i_2}^r$. That is, when $Q_{i_1}^{r+1} > Q_{i_2}^{r+1}$, there are $\mathcal{N}_{i_1}^r \geq \mathcal{N}_{i_2}^r, u_{i_1}^r \geq u_{i_2}^r$. Theorem 3 is proved. □

From Theorem 3, it is known that when the accumulated extra frozen rewards $\mathcal{F}_i^r > 0$, no matter whether the quality of the data in the previous round is good or not, if the participant does not submit high-quality data in the next round, the absolute value of the negative utility will be more significant. Thus, the total utility is smaller. To avoid losses and improve the utility, accumulated extra frozen rewards must be unfrozen. Participants must enhance the data quality submitted in the next round to reach the unfreezing threshold for the platform to issue an extra reward.

The total utility U^r of the platform is the difference between the total value of tasks completed by all participants and the total payment paid by the platform, expressed as Formula (18).

$$U^r = \sum_{t_i \in \mathbb{T} and p_i \in W^r} v_i - \sum_{p_i \in W^r} \mathcal{A}_i^r \tag{18}$$

3.4. A Detailed Example

This section will show the participant's selection process with specific examples and compare the situation without PSM-RD. According to the parameter values given in [64], there are $\alpha = \beta = 0.88, \lambda = 2.25$.

Assuming that the task sets is $T = \{t_1, t_2, t_3, t_4, t_5\}$, the participant set is $P = \{p_1, p_2, p_3, p_4, p_5, p_6\}$ and the task value sets is $V = \{v_1, v_2, v_3, v_4, v_5\} = \{5, 7, 10, 9, 14\}$. The specific information is shown in Table 2.

Table 2. Task and user's pricing.

Properties	T_i^r	b_i	V_i
p_1	t_1, t_2	3	12
p_2	t_1, t_2, t_3	6	22
p_3	t_2, t_3	4	17
p_4	t_1, t_2, t_4	5	21
p_5	t_3, t_4	4	19
p_6	t_4, t_5	7	23

3.4.1. Participant Selection without Reference Dependence

The specific process for selecting a participant is as follows when the reference dependence is not considered.

Step 1: Calculating the pricing b_i of each user for the unit value ξ_i, then $\xi_1 = \frac{b_1}{V_1} = \frac{3}{5+7} = \frac{3}{12} = 0.2500, \xi_2 = \frac{b_2}{V_2} = \frac{6}{5+7+10} = \frac{6}{22} \approx 0.2727, \xi_3 = \frac{b_3}{V_3} = \frac{4}{7+10} = \frac{4}{17} \approx 0.2353, \xi_4 = \frac{b_4}{V_4} = \frac{5}{5+7+9} = \frac{5}{21} \approx 0.2381, \xi_5 = \frac{b_5}{V_5} = \frac{4}{10+9} = \frac{4}{19} \approx 0.2105, \xi_6 = \frac{b_6}{V_6} = \frac{7}{9+14} = \frac{7}{23} \approx 0.3043$;

Step 2: Eliminating users with $\xi_i = 0$, and sort the values of ξ_i from small to large. If the user's ξ_i values are the same, sort them according to the i value from small to large, then the order of ξ_i is $\xi_5, \xi_3, \xi_4, \xi_1, \xi_2, \xi_6$;

Step 3: Accumulating the value of ξ_i of each user in turn until $\sum_{i=1}^{6} \xi_i > 1$. According to Table 2, there are $\xi_5 + \xi_3 + \xi_4 + \xi_1 = 0.9339 < 1, \xi_5 + \xi_3 + \xi_4 + \xi_1 + \xi_2 = 1.2066 > 1$;

Step 4: the sets of participants $W^r = \{p_1, p_3, p_4, p_5\}$. That is, the number of participants is 4.

The user's pricing process is shown in Figure 4.

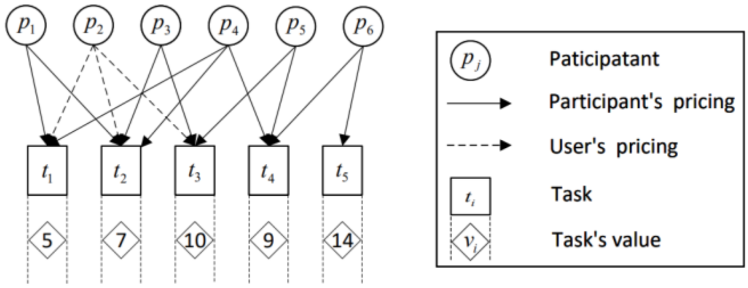

Figure 4. Pricing without reference dependence.

3.4.2. Participant Selection with Reference Dependence

It is known from Theorem 2 that the pricing b_i^r when reference dependence is considered is smaller than the pricing $\tilde{b_i^r}$ when reference dependence is not considered. In order to simplify the calculation, assuming that $\tilde{b_i^r} = b_i^r + 1$, then the user's pricing are $\{b_1, b_2, b_3, b_4, b_5, b_6\} = \{2,5,3,4,3,6\}$. the specific process for selecting a participant is as follows.

Step 1: Calculating the pricing b_i of each user for the unit value ξ_i, then $\xi_1 = \frac{b_1}{V_1} = \frac{2}{5+7} = \frac{2}{12} \approx 0.1667, \xi_2 = \frac{b_2}{V_2} = \frac{5}{5+7+10} = \frac{5}{22} \approx 0.2272, \xi_3 = \frac{b_3}{V_3} = \frac{3}{7+10} = \frac{3}{17} \approx 0.1765, \xi_4 = \frac{b_4}{V_4} = \frac{4}{5+7+9} = \frac{4}{21} \approx 0.1905, \xi_5 = \frac{b_5}{V_5} = \frac{3}{10+9} = \frac{3}{19} \approx 0.1579, \xi_6 = \frac{b_6}{V_6} = \frac{6}{9+14} = \frac{6}{23} \approx 0.2609;$

Step 2: Eliminating users with $\xi_i = 0$,and sort the values of ξ_i from small to large. If the user's ξ_i values are the same, sort them according to the i value from small to large, then the order of ξ_i is $\xi_5, \xi_3, \xi_1, \xi_4, \xi_2, \xi_6;$

Step 3: Accumulating the value of ξ_i of each user in turn until $\sum\limits_{i=1}^{6} > 1$. According to Table 2, there are $\xi_5 + \xi_3 + \xi_1 + \xi_4 + \xi_2 = 0.9188 < 1, \xi_5 + \xi_3 + \xi_1 + \xi_4 + \xi_2 + \xi_6 = 1.1797 > 1;$

Step 4: the sets of participants $W^r = \{p_1, p_2, p_3, p_4, p_5\}$. That is, the number of participants is 5.

The user's pricing process is shown in Figure 5.

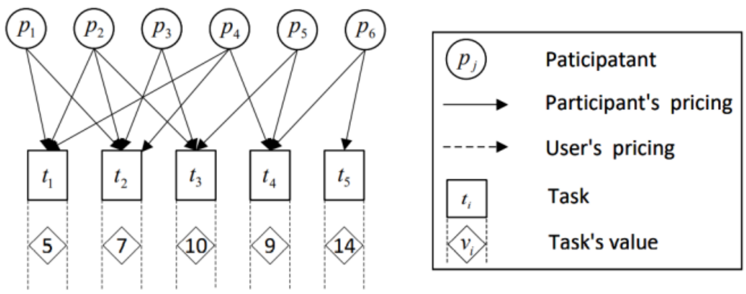

Figure 5. Pricing with reference dependence.

The above process shows that the number of participants in PSM-RD is more significant than that without considering reference dependence. Since each participant will complete at least one task, the task completion rate increases, proving the effectiveness of PSM-RD.

4. Simulations and Evaluations

To illustrate the effectiveness of PSM-RD and QAM-LA, this section will verify the theory through simulation experiments and compare it with the traditional ABSee mechanism [65]. ABSee selects participants under budget constraints. It maximizes the generated value by completing tasks and improves sensing data quality. Section 4.1 will introduce the environment settings of simulation experiments, and Sections 4.2–4.4 will analyze the experimental results.

4.1. Experimental Environment Settings

This simulation experiment runs on the open-source Repast platform [66]. To ensure rationality and fairness, this experiment's experimental environment and parameter settings are the same as those of ABSee. Table 3 shows the details.

Table 3. Experimental parameter settings.

Symbol	Value	Description
η_i	[1,5] Uniform distribution	Average cost per task of p_i
C_i	$\eta_i * \lvert T_i \rvert$	The sensing cost of p_i
χ_i	[1,5] Uniform distribution	The weight of the task t_i
d	50	Distance threshold
θ	(0,1)	Budget allocation factor
λ	(0,1)	Exogenous reference point
γ	(0,1)	Endogenous reference point

Figure 6 shows the topology. Users and tasks are randomly distributed in the range of 1 km $\times$ 1 km, and the effective distance for the user to complete tasks is 50 m, and the same task can be selected and completed by multiple users. For each task, the quality of the completed data obeys a uniform distribution between (0, 1), and all experimental results are the average value over 100 runs.

4.2. Number of Participants

First, we explore the influence of θ and λ on the number of participants, with more participants indicating higher task completion rates. When $\lambda = 0$, the participant may not receive any extra reward. When $\lambda = 1$, the mechanism will fail. Therefore, $\lambda \in (0, 1)$. Similarly, when $\theta = 0$, the participant may not receive any extra reward; the mechanism will fail when $\theta = 1$. Therefore, $\theta \in (0, 1)$. The fixed number of users is 100, and Figure 7 shows the change in the number of participants when both θ and λ are in (0, 1).

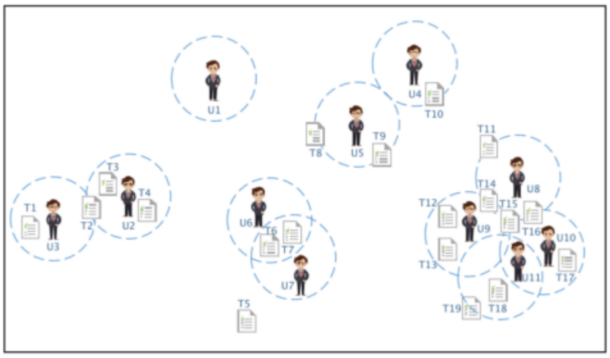

Figure 6. Experimental environment topology diagram.

It is known from Figure 7 that the number of participants gradually decreases as θ trends to 0 and λ trends to 1. When θ trends to 1 and λ trends to 0, the number of participants gradually increases, and the task completion rate is the highest under this condition. If $\theta \in (0, 0.5]$ and λ are increased, the proportion of extra reward to the total platform budget is relatively large because the user's pricing is relatively high, and the number of participants that can be selected gradually decreases. When θ gradually increases, and λ gradually decreases, the number of participants gradually increases, which means that the user's pricing decreases. Moreover, when θ increases to 0.5 and λ decrease to 0.5, the growth rate of the number of participants gradually increases. Then, we explore the influence of the budget allocation factor θ on the number of participants. Setting that number of tasks to 100 and the platform budget to 100, Figure 8 shows the relationship between the number of users and the number of participants for different θ values when $\lambda = 0.5$.

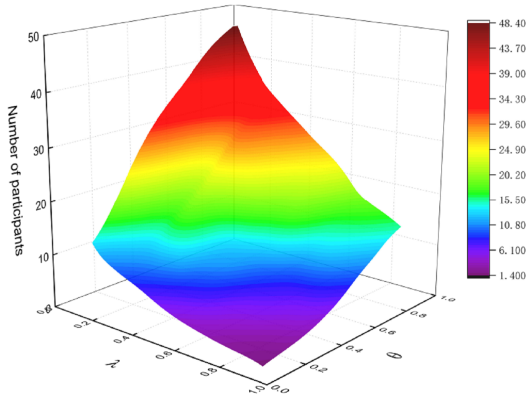

Figure 7. Effects of θ and λ on the number of participants.

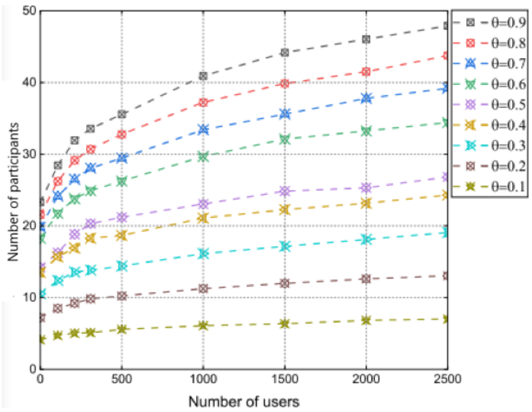

Figure 8. The number of users vs. the number of participants when $\lambda = 0.5$.

It is known from Figure 8 that when $\lambda = 0.5$, the number of participants increases as the number of users increases. When $\theta \in (0, 0.5]$, the number of participants of PSM-RD is relatively tiny; when $\theta \in (0.5, 1)$, the number of participants of PSM-RD increases significantly, and as θ increases, more users are selected. Therefore, we focus on the case of $\theta \in (0.5, 1)$.

Finally, we explore the influence of λ on the number of participants. To ensure the comparability of the experimental results, the number of tasks is set to 100, and the platform budget is set to 100. Figure 9 shows the relationship between the number of users and the number of participants for different λ values when $\theta = 0.5$.

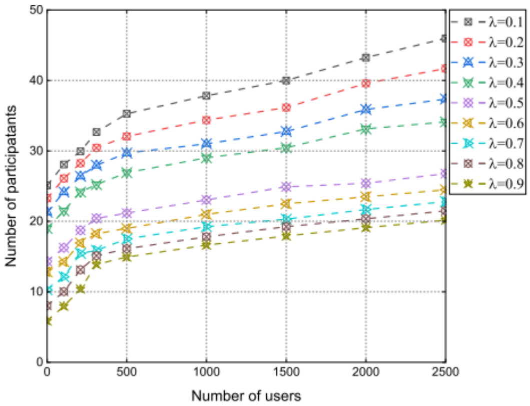

Figure 9. The number of users vs. the number of participants when $\theta = 0.5$.

It is known from Figure 9 that if $\theta = 0.5$, the number of participants increases as the number of users increases. When $\lambda \in [0.5, 1)$, the number of participants of PSM-RD is relatively tiny. When $\lambda \in (0, 0.5)$, the number of participants of PSM-RD is more significant, and as λ decreases, more users are selected. Therefore, we focus on the case of $\lambda \in (0, 0.5)$.

Once users are selected, changes in data quality will be explored. At the same time, other parameters that vary with data quality are analyzed, including total platform payment, and participant utility.

4.3. Task Value

The value $V(s)$ generated by the participant refers to the total value of all completed sensing tasks, mainly affected by task completion rate and data quality. Figure 10 shows the impact of the number of participants on the value generated by the participants when $\lambda = 0.1$ and $\theta \in (0.5, 1)$.

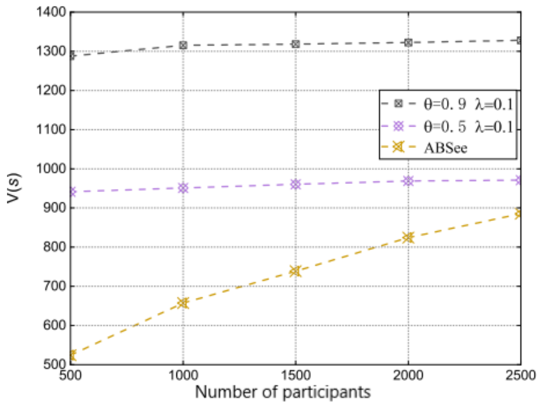

Figure 10. The number of participants vs. $V(s)$ when $\lambda = 0.1$.

Figure 10 shows that if $\lambda = 0.1$ and the number of participants is constant, $V(s)$ in the PSM-RD and the ABSee increases as θ increases, and V(s) in the PSM-RD is larger than the ABSee. When θ is the same, as the number of participants increases, $V(s)$ still increases, but the magnitude of its increase gradually decreases. The reason is that under a specific budget condition and the number of participants reaches 500, and the participants are saturated. At this point, even if the number of users continues to increase, the number of participants will remain relatively high.

Figure 11 shows that if $\theta = 0.9$ and the number of participants is constant, $V(s)$ in the PSM-RD and the ABSee increases as λ increases, and $V(s)$ in the PSM-RD is larger than the ABSee. When λ is the same, as the number of participants increases, $V(s)$ also increases, but the magnitude of its increasing becomes smaller, and the reason is the same as Figure 10.

Comparing Figures 10 and 11, we can see that the general trend of $V(s)$ is consistent, but the influence of λ on $V(s)$ is more significant than that of θ on $V(s)$. Figures 12–15 will explore how the value generated by the participant changes as the number of tasks increases or the budget increases.

It is known from Figure 12 that when λ is the same, if $\theta = 0.9$, the more the number of tasks, the greater the $V(s)$. In this figure, when the number of tasks is in [100,200], the growth of $V(s)$ is the fastest, and the growth trend gradually decreases as the number of tasks increases. The reason is that when the number of tasks reaches 200, the platform's cost is relatively close to the platform budget. Even if the number of tasks increases, the platform cannot select more participants.

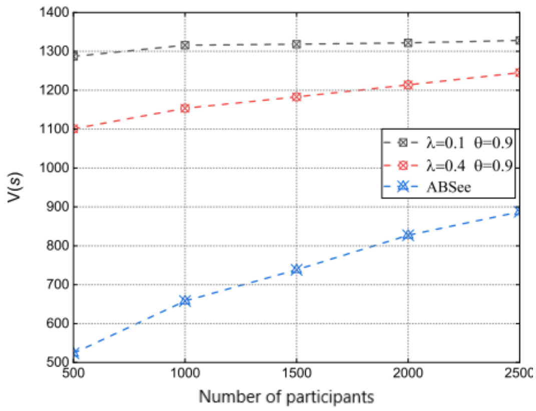

Figure 11. The number of participants vs. $V(s)$ when $\theta = 0.9$.

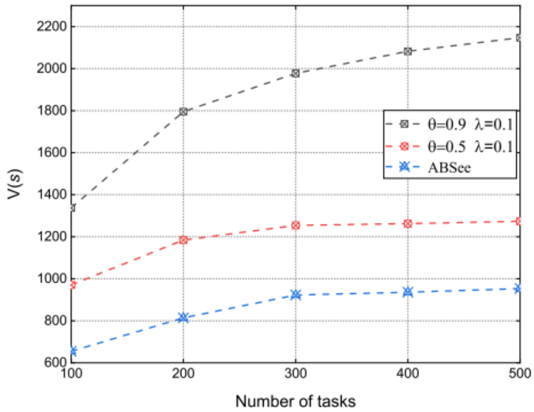

Figure 12. The number of tasks vs. $V(s)$ when $\lambda = 0.1$.

Figure 13 shows that when θ is the same, if $\lambda = 0.1$, the more the number of tasks, the larger the $V(s)$. In this figure, when the number of tasks is in [100,200], the growth of $V(s)$ is the fastest, and the growth trend gradually decreases as the number of tasks increases. The reason is the same as in Figure 12.

Comparing Figures 12 and 13, we can see that the effects of θ and λ on the trend of $V(s)$ are the same when the number of tasks is the same. The larger θ, the larger $V(s)$ generated by the participants. Moreover, λ has a more significant impact on $V(s)$.

For the fairness of the comparison, when discussing the relationship between the budget and the value generated by the participant, we set the number of tasks to 100 and the number of participants to 1000, as with ABSee.

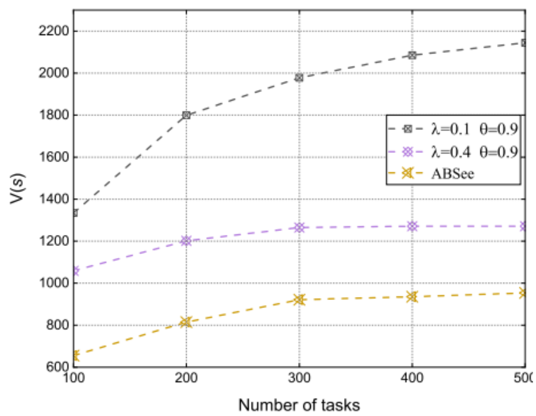

Figure 13. The number of tasks vs. $V(s)$ when $\theta = 0.9$.

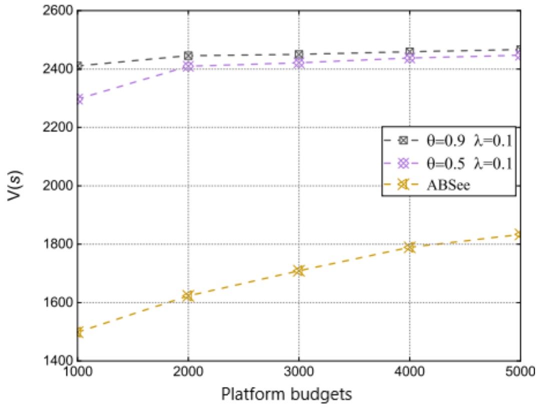

Figure 14. Platform budgets vs. $V(s)$ when $\lambda = 0.1$.

It is obtained from Figures 14 and 15 that when G $\in$ [1000,2000], $V(s)$ grows faster. When G > 2000, even if G increases again, $V(s)$ increases less. Because in the area of 1 km $\times$ 1 km, when the number of participants is 1000, the participant density is high, and most tasks can be completed. So when G > 2000, increasing the budget does not increase the number of tasks that can be completed. Therefore, $V(s)$ growth is negligible. At the same time, comparing Figures 14 and 15, we can see that the general trend of $V(s)$ is consistent, but the influence of λ on $V(s)$ is more significant than that of θ on $V(s)$. Based on the above analysis, it is known that the participant generates more value after applying PSM-RD than ABSee.

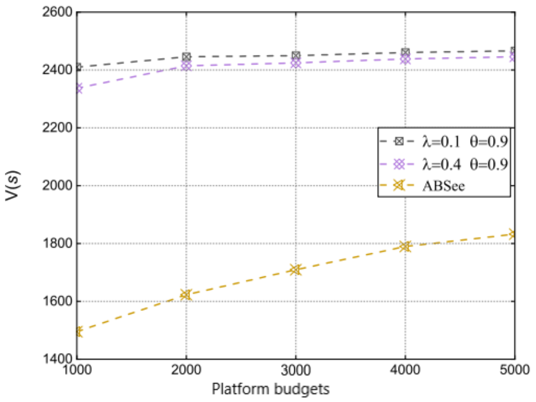

Figure 15. Platform budgets vs. $V(s)$ when $\theta = 0.9$.

Figure 16 shows the change in data quality based on the condition with the highest number of participants, i.e., θ = 0.9 and λ = 0.1.

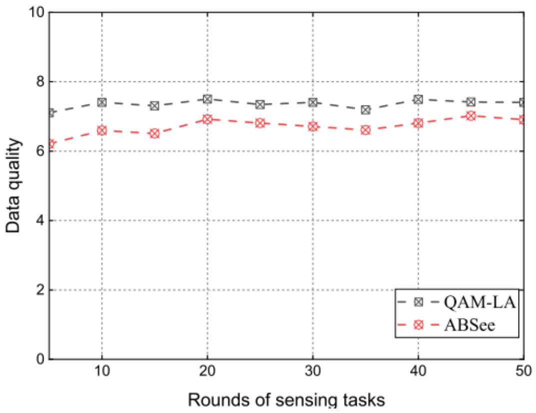

Figure 16. The comparison of data quality between QAM-LA and ABSee.

It can be seen from Figure 16 that the data quality of the AB-See mechanism fluctuates between [6, 7], and the data quality of QAM-LA is stable above 7. That is, the data quality in QAM-LA is better than that of the ABSee mechanism. The reason is that participants with substandard quality in QAM-LA will improve the data quality in the next round, so the overall level of data quality is higher than that of the ABSee mechanism. If more participants did not submit high-quality data in certain rounds, the average data quality decreased slightly. In the next round, there will be more participants to improve the data quality, so there will be a fluctuating trend.

Figure 17 shows the influence of number of participants and number of tasks on the total utility of participants.

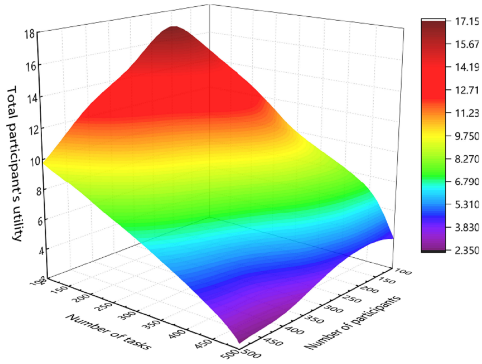

Figure 17. The influence of the number of participants and number of tasks on the total utility of participants.

It can be seen from Figure 17 that when the number of participants is constant, the total participant utility negatively correlates with the number of tasks. The reason is that when a single participant selects many tasks, the probability of submitting high-quality data is relatively low. The total loss value increases negative utility, which leads to a decrease in total utility. When the number of tasks is constant, the number of participants increases as the number of users increases, and the sum of the negative utility generated increases, resulting in a decrease in the total utility of participants.

4.4. Total Platform Payment

In the ABSee mechanism, the total platform budget is set at 50 and 100, respectively, and the total platform payment is analyzed. Under the same setting conditions, the total platform payment of QAM-LA is shown in Figure 18.

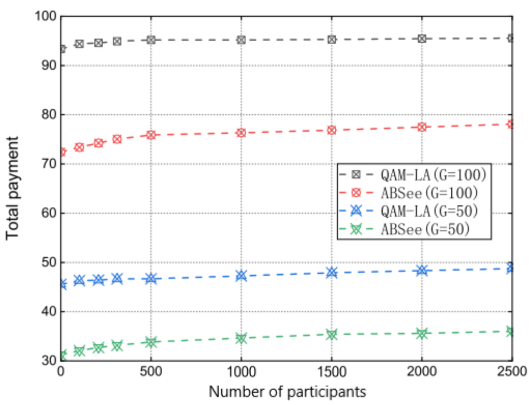

Figure 18. The relationship between the number of participants and the total platform payment.

It can be seen from Figure 18 that when the total platform budget is 50 or 100, the total platform payment increases with the number of participants. Under QAM-LA, the total platform payment is close to the platform budget. On the premise of making full use of the platform budget, it can create more value for the platform.

Figure 19 shows the influence of the number of participants and tasks on the total utility of the platform.

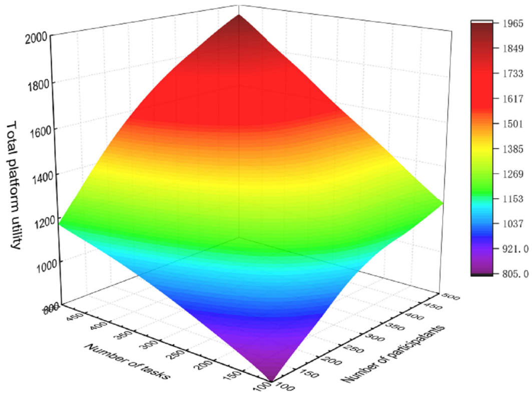

Figure 19. Effects of the number of participants and the number of tasks on the total utility of platform.

It can be seen from Figure 19 that when the number of participants is constant, the total utility of the platform increases as the number of tasks. The reason is that when the number of tasks is larger, the average number of tasks completed by the participant is larger, and more value is created for the platform, so the total utility of the platform is higher. When the number of tasks is constant, the total utility of the platform increases as the number of participants. The reason is that, as the number of users increases, the number of participants will also increase. When more tasks are completed, the platform creates more value, so the total utility of the platform is higher.

In this section, we use the same experimental parameter settings as the comparative paper [65] and ensure that the evaluation method for data quality is the same. This paper explores the impact of various factors on the incentive effect in this mechanism, such as θ, λ, number of users, etc. Then this paper compares the ABSee mechanism and analyzes the results regarding participant number, task value, data quality, total platform payment, etc. The simulations and evaluations show that the PSM-RD mechanism can increase the number of participants, thereby increasing the total value of completed tasks and the QAM-LA mechanism can improve data quality; however, the platform's reward expenditure is higher in this mechanism than in the ABSee mechanism. This is because increasing the number of participants also means more rewards, and higher data quality also raises the spending on extra rewards. The platform's budget has been fully utilized. In summary, the mechanism proposed in this paper has an overall better incentive effect than the ABSee mechanism.

5. Conclusions

Addressing the problem of low-quality data submitted by participants, this paper designs incentive mechanisms under budget constraints, including the PSM-RD and the QAM-LA. The simulation results show that, compared with the ABSee mechanism, data quality has improved by 17%, and the value of completed tasks has increased by at least 40%. In user pricing, the PSM-RD considers the reference dependence, and selects users with the ratio of the user's pricing to the task's value. When paying participants, the QAM-LA determines extra rewards based on the data quality, using the participant's sensitivity factor to improve the participant's data quality. However, more participants mean more payment expenses and higher data quality means more extra rewards. Therefore, the mechanism proposed in this paper also increases budget expenses to some extent.

In addition, this paper only considers the endogenous and exogenous reference points, and multiple reference points may influence individual decision-making behavior [67,68].

In this case, whether multiple reference points will still impact user decision-making in the same way still requires further research. Furthermore, the results presented are generated at each specific value of λ and θ. Future research will also focus on finding a combined search algorithm for these two parameters to improve task completion rate and data quality.

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