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Familiar Paths Are the Best: Incentive Mechanism Based on Path-dependence Considering Space-time Coverage in Crowdsensing

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Abstract—Location Dependent Mobile Crowdsensing (LDMC) often needs to collect data at different time points in various regions to ensure the coverage of sensing data. An incentive mechanism is needed to encourage participants to move to sparse areas and improve coverage. However, there are two problems: 1) most incentive mechanisms assume that the participants can get accurate information about tasks; 2) those mechanisms encourage participants through absolute utility so that the platform can obtain an improvement of incentive effect by increasing the reward. However, nodes usually get inaccurate information in reality. Moreover, behavioral economics finds that decision-making is often affected by relative utility rather than absolute utility. Path-dependence means that choices made on the basis of transitory conditions can persist long after those conditions change, which can solve the above problems. This study uses cognitive bias and the reference effect to explain the principle of path-dependence, and proposes a mechanism called Task Coverage promotion based on Path-dependence (TCPD). TCPD cultivates the cognitive bias of participants, causing an overestimation of expected utility. Then, it sets dynamic reference points to prevent participants from quitting early. The simulation results show that TCPD can improve the coverage and effectiveness of the platform.

Index Terms—CrowdSensing,Incentive Mechanism,Path-dependence,Cognitive Bias,Reference effect

1 Introduction

LDMC is a sensing method that requires participants to move to a specific location in order to accomplish a data collection task [1], and the quality of its sensory data is closely related to the level of coverage in the spatial and temporal domains. Currently, LDMC is widely used in a variety of applications such as air quality monitoring [2][3], traffic monitoring [4][5], and smart cities [6][7][8]. For example, in smart city parking, the timely and accurate information about parking space is directly related to the parking experience of service requestors. In order to expand the level of spatiotemporal coverage, improve the quality of data, and help upper-level applications make accurate decisions, the platform faces the following problems: First, it is necessary to encourage participants to move to each task point in the monitoring area to achieve stable and long-term data transmission[9][10]. Second, The distribution of participants within regions tends to be often uneven[11], and the number of participants in remote areas is not sufficient for the sensing task [12]. Finally, the cost of recruiting new participants is higher than the cost of continuously maintaining older participants [13]. Therefore, it is necessary to motivate participants to move to improve their spatial coverage and maintain long-term participation.

To solve the problem of spatiotemporal data collection, the current incentive mechanism motivates participants to participate in remote area sensing tasks through monetary [1] or non-monetary incentives [14]; however, these incentive mechanisms generally have the following two problems:

First, most of these incentive mechanisms are based on the assumption that decision-making information is accurate and complete, that is,participants can accurately grasp complex and variable task and reward information in actual environments [9]. A few mechanisms that consider incomplete information ignore the deviation in participants' sensing of objective probability caused by incomplete information. Participants may make incorrect estimates of decision-making conditions so as to result in a mechanism with a lower actual effect than expected [15]. Behavioral economics has found that participants are often affected by this kind of incomplete information, resulting in a bias between the conditions on which the decision is based and the objective probability, that is, cognitive bias [16][17].Cognitive bias refers to the systematic deviation from rationality caused by factors such as incomplete information in judgment or decision-making. Platforms can utilize cognitive bias to generate positive effects that are beneficial to themselves through well-designed mechanisms. Inspired by this, the paper utilizes incomplete information to construct probability bias to motivate participants to participate in tasks in remote areas and improve task coverage.

Second, most of these incentives do not take into account the long-term incentive for participating in remote area sensing tasks, resulting in low data coverage in those areas. A few mechanisms that take into account the long-term incentive assume that a participant's decision is determined by the absolute value of utility [9]. That is, the platform needs to increase the reward to get the incentive effect corresponding to the input [1]. In scenarios where there is a high demand for data in remote areas, the existing mechanisms are limited by budget, and their actual effect will be lower than their theoretical effect. However,

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behavioral economics studies have shown that decision-makers value judgments are not based on absolute criteria, but are influenced by relative value to specific conditions and are not proportional to absolute value, which is called reference effect [18]. Specific conditions are called reference points. Thus, under the influence of reference points, the higher reward may not necessarily bring greater utility. Reasonable use of reference points may get better results in the case of low input.Inspired by this, the paper introduces reference points and utilizes relative utility to influence participants' decisions, achieving the goal of motivating participants to participate in remote area tasks for a long time without increasing platform costs.

Path-dependence [19] in life is characterized by long-term sustainability with little additional investment and maintenance, which fits well with the goal of motivating participants in LDMC to provide stable, long-term data in remote areas. In life, even if the new road is closer, people are used to walking the old road, so many people still unconsciously follow the original way and ignore that the old road is farther. Path-dependence implies that once people make a certain decision, they choose the last decision-making method when they encounter similar problems. Even if the initial decision is not the best choice in most cases, path-dependence can still occur. An analysis of path-dependence revealed that the formation of path-dependence includes the processes of cultivating and maintaining habits.

Therefore, the proposed path-dependence mechanism is divided into Path Training (PT) and Path Maintenance (PM) stages. In addition, we introduce the cognitive bias theory and reference effect theory of behavioral economics to construct a two-stage incentive mechanism. In the PT, participants form cognitive bias values through the information difference between the actual information and published information. And in each round of tasks, the value is continuously strengthened. Then the participant cognitive bias value is applied to the utility function to make the participant make a favorable decision for the platform and complete the training of the path. Because the improvement in the platform's utility reduces the utility of the participants, it is necessary to maintain the path-dependence of the participants in the PM. Thus, this study designed a mechanism to prevent participants from exiting the platform.

In summary, this study proposed an incentive mechanism that includes a Path Cultivation mechanism based on Bias Learning (PCBL) and a Path Maintenance mechanism based on the Reference Effect (PMRE). The main contributions of this study are as follows:

1. Cognitive bias theory is introduced into MCS, and PCBL is proposed by establishing the mapping of life instances to MCS. PCBL affects participants' cognition by creating an information difference; therefore, causing participants to overestimate the probability of obtaining additional rewards. This is done to cultivate participants' path-dependence on choosing tasks in remote areas and improve spatial coverage.

2. Reference effect is introduced into the MCS, and PMRE is proposed based on the cultivated cognitive biases. The path-dependence function is set in the PT and PM to quantify the participants' degree of path-dependence. Through the cultivation of PT and maintenance of PM, participants can maintain their dependence on the task, improve the coverage rate, reduce the withdrawal of participants, and achieve long-term incentives.

The rest of this paper is organized as follows: Section 2 presents research on related incentive mechanisms based on traditional economics in LDMC, related theories of path-dependence, cognitive bias, and reference effect theory from behavioral economics. Section 3 introduces a system model for LDMC and the proposed system,which mainly consists of PCBL and PMRE. Section 4 provides a detailed introduction to TCPD.Section 5 demonstrates that TCPD plays a significant role in improving the task coverage rate in LDMC, the user participation rate, and the overall utility of the platform through simulation experiments.Section 6 is a summary of the entire paper.

2 Related Work

This section introduces existing incentive mechanisms based on traditional economics in LDMC and the basic theories of related behavioral economics.

2.1 Research on Incentive Mechanism Based on Traditional Economics

In LDMC, the platform needs to collect the sensing data of various locations in the area at different times; therefore, the main goal of incentives is to improve the coverage of data collection and the retention rate of participants.

Incentives are provided through relevant mechanisms to improve data coverage. In [1], tasks were divided into popular and unpopular according to their location, and task coverage was improved by bundling different types of tasks. [20] adopted a monotonically computable approximation algorithm for task assignment and proposed a compensation algorithm based on proportional sharing rules. [21] considered the inequality of tasks owing to different locations and times and proposed a two-level heterogeneous pricing mechanism to balance the task selection of participants. [22] assigned tasks according to participants' locations and capacities, proposed a real single-round auction, and designed an online algorithm based on each auction round. [23] designed a movement-based crowdsensing incentive mechanism for encouraging participants to perform tasks in remote areas. [24] proposed a location-aware incentive mechanism based on reverse auctions to maximize the participants' expected profits and improve their initiative and task coverage. [25] studied the traffic offloading problem of small cells in the case of location dependence based on the Stackelberg game.

Presently, some incentive mechanisms consider the long-term incentives of participants, that is, improving their retention rate while improving data coverage. These studies enable participants to participate in the task for a long time by introducing factors such as historical information[9], reputation[26], virtual points[27], etc. [9] dynamically established task pricing for sparsely populated areas based on location to attract long-term participation from participants. [26] introduced a reputation scoring system into mobile crowdsensing, which improved participants' enthusiasm for participating in tasks. [27] proposed a multi-dimensional participant recruitment model that takes into account historical information such as participants' distance, computing capacity, and remaining device power to improve users' long-term participation rate. [28] proposed an active sensing framework that enables participants to collect data in an active sensing manner, thereby incentivizing long-term participation. [29] proposed a VCG auction strategy based on Lyapunov for participant selection, which incentivizes long-term participation. [30] proposed a new dynamic price incentive mechanism based on reverse auctions to encourage participants to participate. [31] proposed a multi-round crowdsensing mechanism to attract and retain participants in the long term, achieving maximum social welfare. [32] utilized logistic regression technology to mine participant preferences and designed a mechanism WAA based on reverse auctions, which incentivizes participants to participate in long-term tasks in regions of interest based on participant preferences.

However, these incentive mechanisms generally have the following problems. First, most mechanisms ignore the impact of incomplete information [1], while a few consider incomplete information, but they also ignore the participants' misjudgement of factors for decision-making [20][21][22][23]. In the real world, information such as task characteristics and reward methods is uncertain and variable. This kind of information often leads to participants' misjudgement of factors such as the probability, which leads to the mechanism's actual effect being lower than expected [33]. For example, [1] did not consider incomplete information and motivated participants through task bundling, it assumed that participants had complete knowledge of hot and cold tasks. [20][21] considered incomplete information to motivate participants with additional compensation for changes. However, there were changes in task location, time information, and other factors in these two mechanisms. These papers ignored the bias of participants in estimating the compensation probability caused by such information. [22][23] encouraged participants by auction, taking into account incomplete information in the auction process. However, these two mechanisms ignored the impact of task information changes and competitor interference on participants during the auction process, which could lead to bias in estimating the probability of successful bidding.

Second, the vast majority of incentive mechanisms did not consider incentives for long-term participation [20][25]. A few mechanisms that considered longevity also used absolute utility as a participant's utility, assuming that an increase in reward would result in a corresponding improvement [9][26][27][28]. Therefore, to improve the incentive effect, the platform has to increase the spending [11]. In the case of large data requirements in remote areas, the actual effect of existing mechanisms constrained by budget will be lower than its theoretical effect. For example, [21] used modified pricing to motivate participants to participate in data collection tasks, and [25] used game theory to motivate participants to participate in remote area traffic unloading. This kind of incentive mechanism is aimed at optimizing the utility of single-round tasks without considering the long-term participation of users. These mechanisms ignored the greater burden on participants from long-term participation in tasks and did not guarantee a long-term stable supply of sensing data. [9] used dynamic pricing to motivate participants and long-term assignment of high prices to tasks in remote areas. [26] suggested that participants should be encouraged to participate for a long time in the form of reputation, and their reward should be continuously improved for those with high reputation. [27] introduced a multi-dimensional virtual score, which gave long-term incentives by taking all aspects of participant performance into account. Participants with a high the comprehensive evaluation would get higher rewards. These mechanisms were designed to attract participants with absolute utility and were less effective than expected in scenarios with limited budgets.

The path-dependence in life makes businesses and platforms almost without extra cost; therefore, people can ignore the dynamic and changeable conditions, ignore the cost difference, and choose the path of habit, which is often long-term. Cognitive bias and the reference effect in behavioral economics design incentives to explain how path-dependence develops and persists. The next section will introduce related concepts in behavioral economics.

2.2 Research on Behavioral Economics

2.2.1 Cognitive Bias Theory

People's decisions are based on their cognition and experience; their cognition is limited and not completely based on real situations [34]. People think that their decisions are correct, but when their cognition is biased, such as omitting or misjudging important information, the decisions they make deviate from their original intentions.

Several phenomena in life are caused by cognitive bias, such as probability overestimation [35]. Probability overestimation [36] is a phenomenon that occurs when people make decisions under uncertainty. The traditional expected utility theory holds that in the face of uncertain scenarios, people can objectively and rationally estimate the probability and make decisions based on the expected utility [36]. However, behavioral economics finds that people's probability judgments in different situations are subjective and that they make decisions through probability weights instead of using objective probabilities. A calculation method for the probability weight function is proposed, as shown in Formula (1).

$$\pi(p) = \frac{p^{\gamma}}{\left[p^{\gamma} + (1-p)^{\gamma}\right]^{\frac{1}{\gamma}}} \tag{1}$$

The image of the probability weight function $\pi(p)$ is shown in Fig. 1.

It can be observed from Fig. 1 that when the real probability p

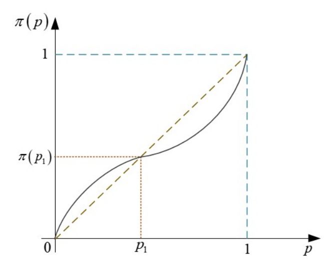

Fig. 1: Basic shape of probability decision function

of the event is small, the probability weight is a convex function, namely $\pi(p) > p$, and an overestimation of the probability occurs, that is, the small probability is overestimated.

2.2.2 Reference effect

Behavioral economics modifies the utility function of traditional economics based on the reference effect and proposes the concept of the value function [37]. Assuming that in the k-dimensional selection bundle, rx_i represents the final reward of the option x_i, and r_i represents the reference point corresponding to the option x_i, then the value function is represented as $v(\Delta_i)$, where $\Delta_i = rx_i - r_i$. The relative value between the final reward and the reference point is considered as the independent variable of the value function. According to the theoretical analysis and experimental verification of behavioral economics [38], the value

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function can be expressed as follows:

$$v\left(\Delta_i\right)=\left\{\begin{array}{c}\Delta_i^{\theta_1}, \Delta_i \geq 0 \\ -\ell\left(-\Delta_i\right)^{\theta_2}, \Delta_i<0\end{array}\right. \tag{2}$$

where ℓ represents the loss aversion coefficient, which is a linear factor representing the participant's sensing of the relative value below the reference point, and $\ell > 1$. θ_1 and θ_2 denote the exponential factors for participants' sensing of relative values above and below the reference point, respectively.

The basic shape of its function is shown in Fig. 2.

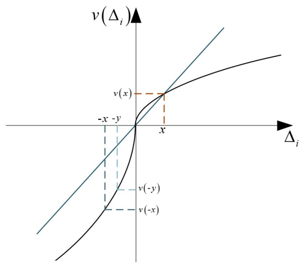

Fig. 2: Basic shape of a value function

As shown in Fig. 2, when $\Delta_i \geq 0$, that is, when the participant's utility is higher than the reference point, the change of $v\left(\Delta_i\right)$ is relatively gentle, and when $\Delta_i < 0$, that is, when the participant's utility is lower than the reference point, the change of $v\left(\Delta_i\right)$ is faster, showing a rapidly declining trend [39]. This shows that the participants were more sensitive to their relative value and the reference point in the face of loss.

Behavioral economics introduces the value function into the utility calculation and modifies the utility formula to $U\left(rx_i \mid r_i\right) = \omega u\left(rx_i\right) + (1-\omega) v\left(\Delta_i\right)$, where $u\left(rx_i\right)$ represents the final reward and ω represents the weight between the final and relative reward [40].

In summary, theoretical research on behavioral economics is relatively mature, some problems in traditional economics have been corrected, and new perspectives have been proposed to explain economic phenomena more reasonably and effectively. However, no relevant combinations exist in the design of incentive mechanism algorithms in LDMC. In summary, no previous study has examined path-dependence on MCS to solve the problem of long-term incentives for participants at a low cost in situations of dynamic and uncertain information. This study used cognitive bias and reference effect to improve the incentives for data coverage and participant retention.

3 System Model

In this section, the proposed system model is described. Section 3.1 describes the proposed physical model. Section 3.2 provides real-life examples and mapping in MCS. Section 3.3 introduces a logical model and explains the logical process of TCPD.

3.1 Physical Model

Fig. 3 shows the cluster-aware physical model applied using TCPD. The platform divides tasks into Remote Area Tasks (RAT) and Hot Area Tasks (HAT) according to the density of the surrounding participants. Each task requires multiple measurements, and each participant could only select one target task at a time [9].

The specific physical process of TCPD is as follows:

①The platform publishes Task Set $ta = \{ta_1, ta_2, \ldots, ta_m, \ldots, ta_M\}$. The m^{th} task contains task information $\{\rho_{ta_m,j}, Mea_{ta_m}, Fl_{ta_m},\}$, where $\rho_{ta_m,j}$ represents the density of participants around the j^{th} turn of a task, Mea_{ta_m} denotes the number of measurements remaining, and Fl_{ta_m} denotes the flag bits. $Fl_{ta_m} = 0$ denotes HAT (when $\rho_{ta_m,j} > \tau^d_{ta_m,j}$), and $Fl_{ta_m} = 1$ denotes RAT (when $\rho_{ta_m,j} > \tau^d_{ta_m,j}$), where $\tau^d_{ta_m,j}$ is the density threshold set by the platform.

②In participant set $\mathbb{U} = \{\mathbb{u}_1, \mathbb{u}_2, \ldots, \mathbb{u}_N\}$, participants were divided into PT and PM participants according to the PTSA algorithm in PCBL. Participant $\mathbb{u}_i$ evaluated all the tasks, submitted the target task ta_m of their choice, and quoted ta_m and $b^{ta_m}_{i,j}$ for the target task.

③The platform counts $b^{ta_m}_{i,j}$ and $d^{ta_m}_{i,j}$ received by each task and calculates the competitiveness evaluation function value $T^{ta_m}_{i,j}(\cdot)$ of the participants to identify the selected participants for each task.

④The winner goes to the corresponding task location for data collection and returns the measured data to the platform, which updates the participants in the PT and PMRE phases according to the PCBL and PMRE, respectively.

⑤The platform pays for the tasks according to the type of tasks the $\mathbb{u}_i$ receives and the stage which it is in, PCBL pays for the $\mathbb{u}_i$ in the PM stage, and PMRE pays for the $\mathbb{u}_i$ in the PT stage.

This section describes the process by which the mechanism operates in a real-world physical scenario. The corresponding relationship with the instance and the logical process of the mechanism are given in Sections 3.2 and 3.3, respectively.

3.2 Instance Mapping

In this study, a classic case of route dependence and the current process for determining the standard gauge of railways are introduced.

Modern standard gauges are based on the width of a horse's butt. The earliest railways were built in England, with the width of a horse's butt. Subsequently, the UK established this gauge as a standard gauge for its transport interests, which led to a large number of horse-butt width gauges built by rail companies worldwide, forming path-dependence [32]. In the subsequent railway construction process, because the horse-butt width gauge railways have been used on a large scale, using the new gauge would incur higher construction, common rail, and other costs. Most builders still choose the horse-butt width as the gauge, making this width of railways used today and becoming the standard gauge worldwide.

Fig. 4 shows the mapping between the establishment of the rail gauge and the application of route dependence in crowdsensing. Step 1 shown in the top half of Fig. 4 indicates that the initial construction of the railroad track was affected by the width of the horse's buttocks, thus completing the first gauge selection. Steps 2, 3, and 4 indicate that after the construction and operation of multiple railways, the utility of such gauge railways is improved and set to the standard gauge, which promotes subsequent rail construction to form path-dependence. Corresponding to the incentive mechanism of MCS, initially, the participants chose to participate in remote area tasks, and after completing the tasks, they received the promotion of task effectiveness, thus forming path-dependence. Step 5 indicates that subsequent gauge decision-makers will continue to choose this gauge to build

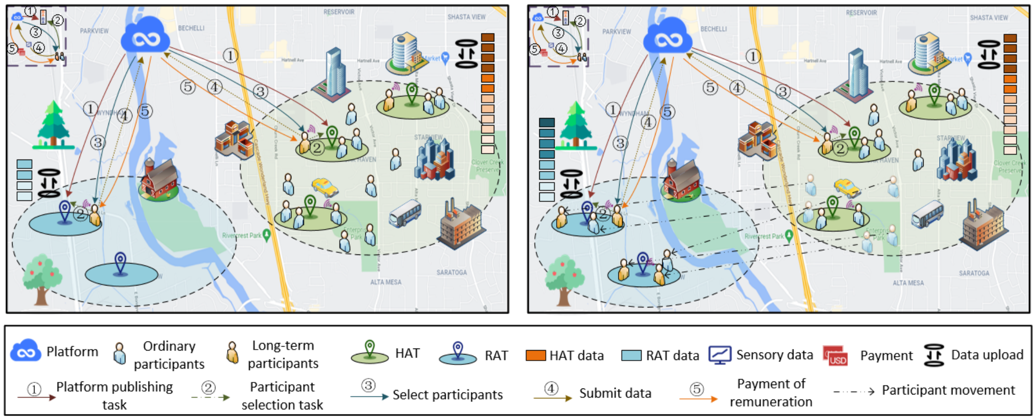

Fig. 3: Physical model diagram of TCPD

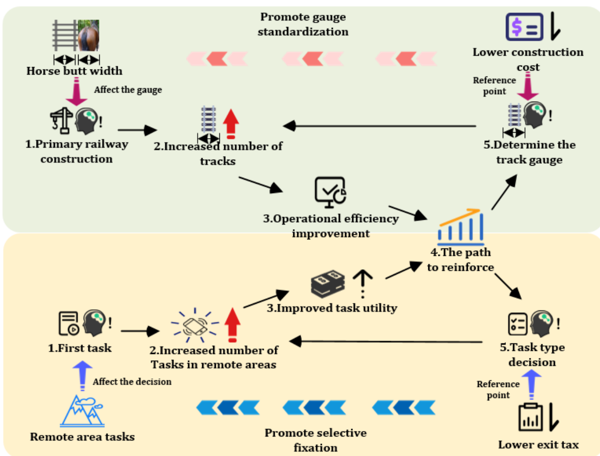

Fig. 4: Path-dependence map

TABLE 1: Parameters Table

Symbol	Definitions
$b_{i,j}^{ta_m}$	$\mathbb{u}_i$ jth round quotation for Target Task ta_m
$d_{i,j}^{ta_m}$	Distance between $\mathbb{u}_i$ jth Round and Task ta_m
$T_{i,j}^{ta_m}(\cdot)$	Competitiveness Evaluation Function for Round J of $\mathbb{u}_i$
$rtr_{i,j}$	Real Reward of $\mathbb{u}_i$ Selecting RATs in Round J of PT Stage
$\alpha_{i,j}^{r}$	Real probability of PT stage $\mathbb{u}_i$ jth round getting dependent reinforcement reward
$Pr_{i,j}$	Expected probability of PT stage $\mathbb{u}_i$ jth round getting dependent reinforcement reward
$Pd\left(n_i^{RT}\right)$	The Judgment Function for Overestimation of $\mathbb{u}_i$ in the jth Round
$ReT\left(Uex_{i,j}^{R}\right)$	Path-dependence Function of $\mathbb{u}_i$ jth Round in the PT stage
$rex_{i,j}$	Expected Reward of $\mathbb{u}_i$ Selecting RATs in Round J of PT stage
τ_i^{pr}	Probability incubation threshold for PT stage $\mathbb{u}_i$
τ_i^{ReT}	Path-dependence incubation threshold for PT stage $\mathbb{u}_i$
$\tilde{\alpha}_{i,j}^{r}$	Real Probability of PM Stage Participants $\mathbb{u}_i$ jth Round Reward Dependency Enhancement
$Pr_{i,j}^{M}$	The Expected Probability of PM Stage Participants $\mathbb{u}_i$ jth Round of Dependent Enhanced Award
$rtr_{i,j}^{M}$	Real Reward of $\mathbb{u}_i$ Selecting RATs in Round J of PM stage
$rex_{i,j}^{M}$	Expected Reward of $\mathbb{u}_i$ Selecting RATs in Round J of PM stage
$ReM\left(Uex_{i,j}^{RM}\right)$	Path-dependence Function of $\mathbb{u}_i$ jth Round in the PM stage
$Pu_{i,j}^{PM}$	$\mathbb{u}_i$ jth round task exit tax base

railways because of the reduced construction and operation costs caused by the increase in the number of standard gauge railways. Corresponding to the type of task that participants in the MCS perform when they are influenced by previous decisions, participants will give up the exit path and continue to pick up sensing tasks, enabling them to steadily participate in remote area tasks for a long time and not easily change their choice or exit the platform.

3.3 Logical Model

This section describes the logical model of the TCPD, starting with the concepts of the key parameters involved in the mechanism.

$T_{i,j}^{ta_m}(\cdot)$ is the participant assessment function, which represents the competitiveness assessment of the information submitted by $\mathbb{u}_i$ to task ta_m in round j. $Pr_{i,j}$ is the incubation probability of $\mathbb{u}_i$ in the PT stage, indicating the probability that the PT stage platform will announce to the participants the issuance of dependent dependency reinforcement reward. $ReT\left(Uex_{i,j}^{R}\right)$ is the path-dependence function of $\mathbb{u}_i$ in the PT stage, which measures the degree of path-dependence of $\mathbb{u}_i$ in the jth round of task. $Pd\left(n_i^{RT}\right)$ is a probability overestimation criterion for $\mathbb{u}_i$ in the PT stage, which is used to determine whether or not participant probability overestimation reaches the threshold. $Pr_{i,j}^{M}$ is the training probability of $\mathbb{u}_i$ in the PM stage,

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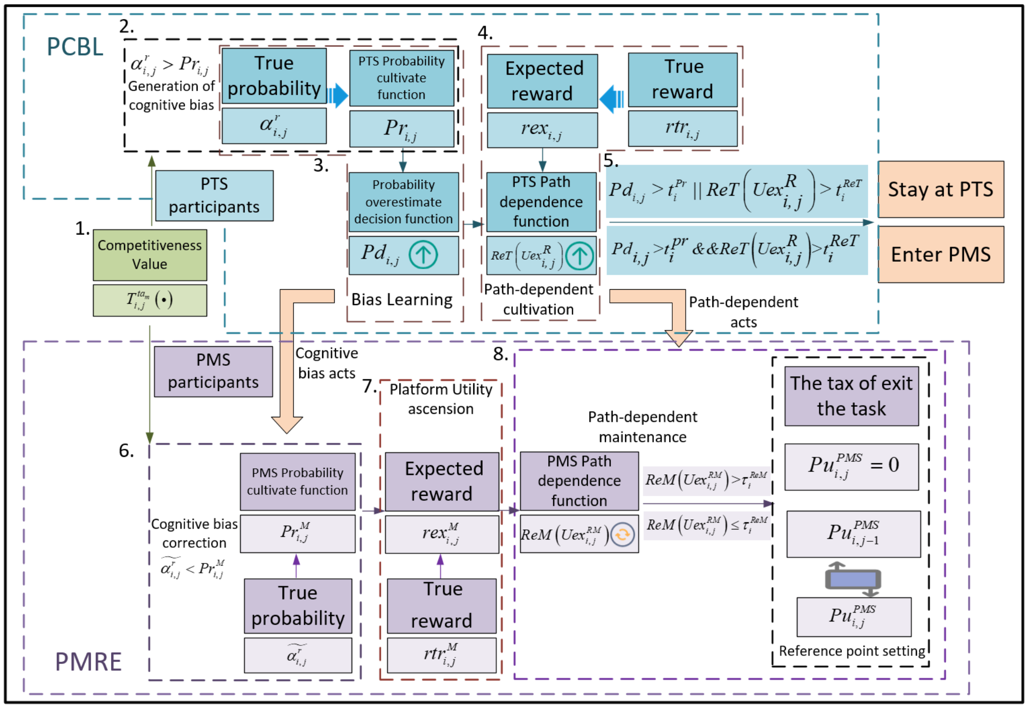

Fig. 5: TCPD logical model diagram

and the platform will be published as the probability that $\mathbb{u}_i$ will depend on the dependency reinforcement reward for the jth round of tasks. $ReM\left(Uex_{i,j}^{RM}\right)$ is a PM stage participant path-dependence function, which is the same as $ReT\left(Uex_{i,j}^{R}\right)$. $Pu_{i,j}^{PM}$ is the task exit tax base value used to measure the deductible part of the reward that $\mathbb{u}_i$ needs to deduct from selecting the jth-round exit platform during the PM stage and handed over to the platform by the participant. The specific settings for these parameters are mentioned in Section 3.

The parameters used to introduce the logical model are listed in Table 1.

Fig. 5 shows a logical model of TCPD, including the PCBL and PMRE used in the PT and PM stages, respectively.

PCBL comprises five steps. In PCBL, the platform first publishes to the participants the participant selection mechanism, reward mechanism, and decision mechanism of the PT stage end. In step 1, participants submit their estimates of all tasks and selected tasks to the platform. The platform calculates $T_{i,j}^{ta_m}(\cdot)$ and selects the winner based on the quotation $b_{i,j}^{ta_m}$ of the tasks selected by the participants in this round and the distance $d_{i,j}^{ta_m}$ from the task location. The setting of $T_{i,j}^{ta_m}(\cdot)$ enables participants to reduce quotation $b_{i,j}^{ta_m}$ and the distance $d_{i,j}^{ta_m}$ from the task location. In step 2, for participants in RATs, participants complete the task, and the platform pays participants $rtr_{i,j}$ according to the reward rules. The real probability of getting a dependent reinforcement reward is $\alpha_{i,j}^r$. Because $\alpha_{i,j}^r > Pr_{i,j}$, participants are nurtured with probability through information difference, resulting in biased learning. For participants in HATs, participants completed the tasks, and the platform paid for them according to quotation $b_{i,j}^{ta_m}$. In Step 3, for the participants in RAT, the platform overestimated the probability of the participants' decision function $Pd\left(n_i^{RT}\right)$. Because of the influence of bias learning, $Pd\left(n_i^{RT}\right)$ tends to increase. In step 4, the platform calculates the participant's $ReT\left(Uex_{i,j}^{R}\right)$ and cultivates the participant's path-dependence level through higher expected utility $rex_{i,j}$, with $ReT\left(Uex_{i,j}^{R}\right)$ increasing trend. In step 5, the platform determines the participant's probability overestimation decision function $Pd\left(n_i^{RT}\right)$ and path-dependence function $ReT\left(Uex_{i,j}^{R}\right)$. When $Pd\left(n_i^{RT}\right) > \tau_i^{pr}$ and $ReT\left(Uex_{i,j}^{R}\right) > \tau_i^{ReT}$ pass the decision, the participant exits the PT stage and enters the PM stage; otherwise, the participant stays in the PT stage for the next round of tasks.

PMRE consists of three steps: steps 6.7.8. After entering the PM stage, participants were trained in the PT stage deviation learning to produce probability overestimation results, while increasing the value of participant $ReT\left(Uex_{i,j}^{R}\right)$. In step 6, for the participants in RAT, the real probability of getting a dependent reinforcement reward was changed to $\widetilde{\alpha_{i,j}^r}$, $\widetilde{\alpha_{i,j}^r} < \alpha_{i,j}^r$ and participant $Pr_{i,j}^M$ decreased because of $\widetilde{\alpha_{i,j}^r} < Pr_{i,j}^M$. In step 7, for the participants in RATs, participants complete tasks, and the platform pays participants $rtr_{i,j}^M$. Because $rtr_{i,j}^M < rtr_{i,j}$, the platform achieves higher utility in the PM stage, whereas $rex_{i,j}^M > rtr_{i,j}^M$ maintains participant $Pr_{i,j}^M$ through information difference. For participants in HATs, participants complete tasks and the platform pays for them according to quotation $b_{i,j}^m$. In step 8, the platform calculates exit tax $Pu_{i,j-1}^{PM}$ and $Pu_{i,j}^{PM}$ for participants who opt out of the task and $ReM\left(Uex_{i,j}^{RM}\right) < \tau_i^{ReM}$ for two adjacent rounds, using $Pu_{i,j}^{PM}$ as a reference point, and deducts tax $Pu_{i,j-1}^{PM}$ and additional amounts for participants who opt out in this round. If the next exit occurs, the exit tax will be calculated according to standard $Pu_{i,j}^{PM}$. After deduction, the utility of this round of participants is negative, preventing them from exiting. For participants in $ReM\left(Uex_{i,j}^{RM}\right) >= \tau_i^{ReM}$, there is $tax_{i,j} = 0$.

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4 INCENTIVE MECHANISM OF TASK COVERAGE PROMOTION BASED ON PATH DEPENDENCE

This section first introduces PCBL algorithm in Section 4.1, which consists of three parts: participant selection, reward algorithm, and quantification of path-dependence. By setting incentives for participants to move and quote, bias learning can bias participants' sensing tasks of probability and then quantify and determine their path-dependence. Subsection 4.2 describes PMRE, including the participant reward algorithm, exit prevention algorithm, and path-dependence quantification. RATs were maintained through PCBL-cultured cognitive bias, whereas path-dependence and reference effect were used to prevent participants from quitting. Section 4.3 presents a performance evaluation of the mechanism.

4.1 Path Cultivation mechanism based on bias learning

Based on the logical model in Section 3.3, the participants first entered the PT stage to take over tasks. In the PT stage, the platform uses the participants' cognitive bias to establish PCBL based on biased learning to guide and enhance the participants' cognitive bias. PCBL motivates participants in the following four sections.

4.1.1 Increasing Participant Probability in the PT stage

In PT, the platform uses information-gap settings to overestimate and nurture the participant's probability assessment, thereby changing the expected utility of the participant.

The participants enter the PT stage and are trained by the platform to overestimate their probabilities. n_i^{RT} represents the number of times that participant $\mathbb{u}_i$ successfully completed RAT in PT, n_i^{HT} is the number of times that $\mathbb{u}_i$ successfully completed HAT in PT, and j is the jth round. The reward of HAT participants is only the basic task reward $\mathbb{H}b_{i,j}$. The reward $rex_{i,j}$ of RAT participants comprises three parts: basic task reward $\mathbb{R}b_{i,j}$, fixed reward $\mathbb{F}i_{i,j}$ and dependent reinforcement reward $\mathbb{D}r_{i,j}$. Among them, the fixed reward $\mathbb{F}i_{i,j}$ is available to all participants who complete RAT, and the dependent reinforcement reward $\mathbb{D}r_{i,j}$ is the additional reward that the participants have the probability to obtain. In the PT stage, the probability that the platform announces to the participants that the reward $\mathbb{D}r_{i,j}$ for dependence reinforcement is granted is the cultivation probability $Pr_{i,j}$ in the PT stage.

As it is necessary to cultivate the overestimated probability of participants in the PT stage, its initial value should be lower. By introducing a posterior probability and variable weight factors, the information gap is expanded, so that $Pr_{i,j}$ increases continuously in the PT stage and that the participants can overestimate the probability. Therefore, the $Pr_{i,j}$ expression is designed as Formula (3).

$$Pr_{i,j} = \begin{cases} \alpha_1, & \text{if } n_i^{RT} = 0 \\ \frac{1}{\lambda_i + \log\left(n_i^{RT}+1\right)} * \alpha_1 + \left(1 - \frac{1}{\lambda_i + \log\left(n_i^{RT}+1\right)}\right) & \\ * \frac{n_i^{GDT}}{n_i^{RT}}, \text{ if } n_i^{RT} > 0 & \end{cases} \tag{3}$$

where α_1 is the initial probability value of the participant $\mathbb{u}_i$ to obtain the dependence reinforcement reward, n_i^{GDT} is the real number of times that participant $\mathbb{u}_i$ obtains the dependence reinforcement reward $\mathbb{D}r_{i,j}$, and $\frac{n_i^{GDT}}{n_i^{RT}}$ is the probability that participant $\mathbb{u}_i$ actually obtains $\mathbb{D}r_{i,j}$ in the process of participating in the remote area task, that is the posterior probability. To reduce the randomness and improve the stability of the system, the platform controls the posterior probability $\frac{n_i^{GDT}}{n_i^{RT}}$ in the actual task process and keeps it close to the real probability $\alpha_{i,j}^r$, that is, $\frac{n_i^{GDT}}{n_i^{RT}} \to \alpha_{i,j}^r$. $\frac{1}{\lambda_i + \log\left(n_i^{RT}+1\right)}$ is the initial probability weight factor, which represents the impact of the initial probability on the participants, and λ_i is the initial probability weight factor coefficient. As n_i^{RT} increases, $\frac{1}{\lambda_i + \log\left(n_i^{RT}+1\right)}$ decreases. As shown in Formula (3), n_i^{RT} is the number of tasks; therefore, if there is $n_i^{RT} >= 0$, the value range of $\frac{1}{\lambda_i + \log\left(n_i^{RT}+1\right)}$ is $\left(0, \frac{1}{\lambda_i}\right)$. If the platform is set to $\frac{1}{\lambda_i + \log\left(n_i^{RT}+1\right)} \in (0,1)$, that is, $\frac{1}{\lambda_i} < 1$, the value of $\lambda_i > 1$ can be obtained.

The platform announces to participants the probability range I_{PT} of obtaining $\mathbb{D}r_{i,j}$ in the PT phase as the neighborhood centered on $Pr_{i,j}$, that is, $I_{PT} = U\left(Pr_{i,j}, x_p\right)$, where x_p is the radius of the neighborhood and the value of $\alpha_{i,j}^r$ falls into $U\left(Pr_{i,j}, x_p\right)$, that is, $\alpha_{i,j}^r \in U\left(Pr_{i,j}, x_p\right)$. The actual probability of the platform distributing $\mathbb{D}r_{i,j}$ to the participant is $\alpha_{i,j}^r$, and the platform sets $\alpha_{i,j}^r > \alpha_1$. The platform cultivates the overestimation probability of participants through the setting of $Pr_{i,j}$ and $\alpha_{i,j}^r$ and their size relationship. The role of $Pr_{i,j}$ and $\alpha_{i,j}^r$ is discussed through Theorem 1 below.

Theorem 1. In PT, $\forall Pr_{i,j}$ and $\forall \alpha_{i,j}^r$, $Pr_{i,j} < \alpha_{i,j}^r$.

Proof: The proof of Theorem 1 is in Appendix A. □

From Theorem 1, the platform encourages participants to overestimate small probabilities by obtaining deviations between the publication probability and real probability, which depend on the dependency reinforcement reward. By participating in and completing tasks in remote areas multiple times, the real posterior probability of the additional reward received by participants affects their probability sensing, resulting in an overestimation of the probability of obtaining the additional reward.

4.1.2 Path-dependence Cultivation of Participants in the PT stage

According to Section 3.3, the cultivation of path-dependence is closely related to the expected utility of participants. This section improves the expected utility of the participants and cultivates their path-dependence on RAT selection by setting up a reward algorithm and combining it with the cultivation of participant probability in Section 4.1.1.

A.Reward algorithm for PT stage

First, the platform reward method for the PT stage was provided to the participants. $rex_{i,j}$ is expressed as follows:

$$\mathrm{rex}_{i,j} = \mathbb{R}b_{i,j} + \mathbb{F}i_{i,j} + Pr_{i,j} * \mathbb{D}r_{i,j} \tag{4}$$

The base task reward $\mathbb{R}b_{i,j}$ is the quotation submitted by the participants in the bidding process, expressed as $\mathbb{R}b_{i,j} = b_{i,j}^{ta_m}$.

The $\mathbb{F}i_{i,j}$ of the participant is determined by the product of the reward factor $\varsigma_{i,j}$ and the basic fixed reward $\Theta_{i,j}$ in the remote areas of the participant. The higher the reward factor $\varsigma_{i,j}$ in the remote areas, the higher is the $\mathbb{F}i_{i,j}$. Fixed reward $\mathbb{F}i_{i,j} = \varsigma_{i,j} * \Theta_{i,j}$.

$\varsigma_{i,j}$ is the fixed extra reward factor for $\mathbb{u}_i$ during PT, which represents the fixed extra reward factor for participants participating in remote area tasks during PT. $\varsigma_{i,j}$ is related to n_i^{RT} and n_i^{HT} of $\mathbb{u}_i$. To attract $\mathbb{u}_i$ to participate in RAT, $\varsigma_{i,j}$ is positively related to

n_i^{RT} and negatively related to n_i^{HT}. To attract $\mathbb{u}_i$ to move toward sparse areas of participants, $\varsigma_{i,j}$ should be negatively related to $\rho_{ta_{mi},j}$. Therefore, $\varsigma_{i,j}$ is defined as follows:

$$\varsigma_{i,j} = e^{\left(\cos\left(\frac{1}{n_i^{RT}+l_i^{RT}}\right)+\sin\left(\frac{1}{n_i^{HT}+l_i^{HT}}\right)\right)\frac{\min\left(\rho_{ta_{m1},j}\cdots\rho_{ta_{mN},j}\right)}{\rho_{ta_{mi},j}}} \tag{5}$$

where $\rho_{ta_{mi},j}$ represents the density of participants around the task that $\mathbb{u}_i$ takes in round j, and $\rho_{ta_{mi},j} >= 0$. l_i^{RT} and l_i^{HT} represent the $\varsigma_{i,j}$ parameters of RAT and HAT, respectively, to control the size of $\varsigma_{i,j}$. As both n_i^{RT} and n_i^{HT} are integers and greater than or equal to 0, so $0 < \frac{1}{n_i^{RT}+l_i^{RT}} < 1$ and $0 < \frac{1}{n_i^{HT}+l_i^{HT}} < 1$. Let $t_{i,j}$ represent the ratio of the minimum value of $\rho_{ta_{mi},j}$ for all tasks to that of the task $\mathbb{u}_i$ selected in round j, that is, $t_{i,j} = \frac{\min\left(\rho_{ta_{m1},j},\rho_{ta_{m2},j}\cdots\rho_{ta_{mN},j}\right)}{\rho_{ta_{mi},j}}$, which yields $t_{i,j} \in (0,1)$. For participants in the same round of tasks, the sparser the number of participants near the task, the more conducive it is to improving the $\varsigma_{i,j}$. Simultaneously, depending on the nature of the trigonometric functions sin and cos, $\varsigma_{i,j}$ monotonically increases with n_i^{RT} and decreases with n_i^{HT}. Participants in the PT stage accumulated a fixed extra reward factor for tasks in remote areas, whereas the fixed extra reward factors for tasks in popular areas decreased.

When a participant completes the task settlement, the platform asks the participant to submit their predicted probability of receiving a dependent reinforcement reward in the round, and the participant submits a set of $\{ep_{1,j}, ep_{2,j}, \ldots, ep_{i,j}\}$. To induce participants to overestimate, a pilot probability $\widetilde{Pr}_{i,j}$ was set. Base $\Theta_{i,j}$ is related to the relative values of $ep_{i,j}$ and $\widetilde{Pr}_{i,j}$, and the smaller the gap, the larger is the $\Theta_{i,j}$, expressed as follows:

$$\Theta_{\mathrm{i,j}} = \frac{t_{i,j}}{\sqrt{2\pi}\sigma} e^{-\frac{\left|ep_{i,j}-\widetilde{Pr}_{i,j}\right|}{2\sigma^2}} \tag{6}$$

$$\widetilde{Pr}_{i,j} = \begin{cases} \alpha_1, & \text{if } n_i^{RT} = 0 \\ \frac{1}{\lambda_i+\log\left(\mu_t * n_i^{RT}+1\right)} * \alpha_1 + \left(1-\frac{1}{\lambda_i+\log\left(\mu_t * n_i^{RT}+1\right)}\right) \\ * \frac{n_i^{GDT}}{n_i^{RT}}, \text{ if } n_i^{RT} > 0 \end{cases} \tag{7}$$

$\Theta_{i,j}$ increases with $t_{i,j}$, indicating that the farther the participant goes to the task location, the higher the value of $\Theta_{i,j}$. μ_t is the adjustment factor. To accelerate the rate of $\widetilde{Pr}_{i,j}$ changing with n_i^{RT}, set $\mu_t > 1$; therefore, $\widetilde{Pr}_{i,j}$ changes with n_i^{RT} faster than $Pr_{i,j}$, and because $\frac{n_i^{GDT}}{n_i^{RT}} > \alpha_1$, $\widetilde{Pr}_{i,j} > Pr_{i,j}$ is obtained. σ represents the dispersion coefficient of the basic fixed reward. The greater the σ, the greater is the dispersion degree of $\Theta_{i,j}$, and the slower is the decline of $\Theta_{i,j}$ after the deviation between the participant's prediction probability $ep_{i,j}$ and $\widetilde{Pr}_{i,j}$ occurs. The platform makes $\mathbb{F}i_{i,j} < \mathbb{R}b_{i,j}$ by setting the value of σ, and obtains $\mathbb{F}i_{i,j} < e^{2t_{i,j}} * \frac{t_{i,j}}{\sqrt{2\pi}\sigma}$ from Formulas (5) and (7). Because $\mathbb{R}b_{i,j} = b_{i,j}^{ta_m}$ is valid, if $e^{2t_{i,j}} * \frac{t_{i,j}}{\sqrt{2\pi}\sigma} < b_{i,j}^{ta_m}$ is valid, then $\mathbb{F}i_{i,j} < \mathbb{R}b_{i,j}$ must be valid, and the range of σ is $\sigma > e^{2t_{i,j}} * \frac{t_{i,j}}{\sqrt{2\pi} * b_{i,j}^{ta_m}}$.

If the setting of $\Theta_{i,j}$ can affect the expected utility of the participants and make the expected utility of the participants approach the cultivation probability $\widetilde{Pr}_{i,j}$, according to the definition of $\widetilde{Pr}_{i,j}$, the cognitive bias of the participants can be further strengthened to make them overestimate the probability. The influence of Formula (7) on the participant submission $ep_{i,j}$ is discussed in Theorem 2.

Theorem 2. $\forall n_i^{RT}$, $ep_{i,j} \to \widetilde{Pr}_{i,j}$.

Proof: The proof of Theorem 2 is in Appendix B. □

Theorem 2 proves that in each round of tasks, participants will submit $ep_{i,j}$ approaching $\widetilde{Pr}_{i,j}$ to obtain higher $\Theta_{i,j}$. Therefore, the platform can analyze the current estimation of the probability of the participants through the $ep_{i,j}$ submitted by the participants, and judge whether the participants meet the cultivation conditions of overestimation and small probability.

The actual reward of each round for participants shall be calculated according to whether they receive additional reward. To improve the expected reward $rex_{i,j}$ of the participants, the platform sets $\mathbb{D}r_{i,j} = \int_{\rho_{ta_{mi},j}}^{\max\left(\rho_{ta_{m1},j},\rho_{ta_{m2},j},\ldots\rho_{ta_{mM},j}\right)} K_1 * \frac{t_{i,j}}{\sqrt{2\pi}\sigma} d\rho$, where K_1 is the coefficient of reliance on reinforcement reward in the PT stage, and $K_1 > 1$ and $K_1 * \frac{t_{i,j}}{\sqrt{2\pi}\sigma} > 0$ can be obtained; therefore, $\mathbb{D}r_{i,j}$ is negatively correlated with $\rho_{ta_{mi},j}$.

In the PT stage, the platform needs to cultivate the overestimation of the probability of the participants; therefore, the probability of obtaining the actual $\mathbb{D}r_{i,j}$ will be higher than the cultivation probability $Pr_{i,j}$, and the real reward $rtr_{i,j}$ of the participants is expressed as follows:

$$\mathrm{rtr}_{i,j} = \mathbb{R}b_{i,j} + \mathbb{F}i_{i,j} + \alpha_{i,j}^r * \mathbb{D}r_{i,j} \tag{8}$$

where the real probability that the platform setting depends on the reinforcement reward is $\alpha_{i,j}^r = \frac{1}{K_1}$.

After the participants completed the dual cultivation of overestimated small probability and path-dependence in the PT stage, they entered the PM stage to receive the task. Therefore, the final decision of the participants' PT stage is also based on the dual decision of the probability cultivation and path-dependence functions.

B. Determination of overestimation probability in the PT stage

The platform released the probability overestimation judgment formula $Pd\left(n_i^{RT}\right)$ to the participants. The setting of $Pd\left(n_i^{RT}\right)$ should achieve the purpose of stimulating participants to participate in RAT; therefore, it should be accumulated according to the improvement in participant n_i^{RF}. The design $Pd\left(n_i^{RT}\right)$ is shown in Formula (9).

$$Pd\left(n_i^{RT}\right) = \sum_{n=1}^{n_i^{RT}} \frac{1}{\lambda_i + \log n} * \alpha_1 + \left(1 - \frac{1}{\lambda_i + \log n}\right) * \alpha_2 \tag{9}$$

Participants accumulate probability overestimation judgment function values by completing the RAT. The setting of α_1 is shown in Formula (3), and the platform sets the specific value of α_2 to satisfy $\alpha_2 > \alpha_1$. The platform sets the probability judgment threshold τ_i^{pr}, which determines that the participant passes the probability overestimation judgment when $Pd\left(n_i^{RT}\right) > \tau_i^{pr}$, and conversely, fails. $\beth$ is the probability cultivation coefficient. The platform makes $\alpha_2 = ep_{i,j}$ in each round, $ep_{i,j}$ is the expected probability of that participant's submission in the current round and will have an impact on $Pd\left(n_i^{RT}\right)$. Let $\tau_i^{pr} = \sum_{n=1}^{n_i^{RT}} \frac{1}{\lambda_i+\ln_n} * \alpha_1 + \left(1-\frac{1}{\lambda_i+\ln_n}\right) * \beth * \alpha_{i,j}^{tr}$, when $Pd\left(n_i^{RT}\right) \geq \tau_i^{pr}$, the participant's estimation of the probability has been raised into the range needed by the platform to make the participant satisfy the probability nurturing condition.

C. Path-dependence function in the PT stage and its determination

When a participant's path-dependence function value is higher than the threshold value, the participant has completed path-dependence cultivation.

The platform publishes the path-dependence function value $ReT\left(Uex_{i,j}^{R}\right)$ to the participants as a RAT qualification value. When participants accumulate sufficient task qualifications by participating in RAT, they can enter the next stage to receive tasks.

$Uex_{i,j}^{R}$ can be expressed by the participant's compensation minus the cost, $Uex_{i,j}^{R} = rex_{i,j} - c_{i,j}^{ta_m}$.

$c_{i,j}^{ta_m}$ is the cost of $\mathbb{u}_i$'s participation in task ta_m in the jth round as estimated by the platform. In the task, participants needed to bring mobile sensing devices to the designated location first and then complete data collection. Therefore, the cost to the participants is primarily composed of mobile and data collection costs. The mobile cost is related to the distance travelled. The data collection cost is related to the processing capacity and transmission capacity of the device and the cost of information search, which is expressed as $c_{i,j}^{ta_m} = c_{ta_m}^{data} + e^{\vartheta_{i,j}^{ta_m} * d_{i,j}^{ta_m}} - 1$, where $c_{ta_m}^{data}$ represents the data collection cost of ta_m, and $\vartheta_{i,j}^{ta_m}$ denotes the cost coefficient of moving unit distance when participants participate in tasks. The higher the value of $\vartheta_{i,j}^{ta_m}$, the higher the moving cost of participants; consequently, different values of RAT and HAT will be obtained.

According to the mapping in Section 3.2, path-dependence is usually related to the utility and degree. Therefore, $ReT\left(Uex_{i,j}^{R}\right)$ of the platform setting should be positively related to $Uex_{i,j}^{R}$. Specifically, obtaining and repeatedly obtaining higher utility is conducive to strengthening the dependence on the path. Therefore, $ReT\left(Uex_{i,j}^{R}\right)$ was set as the accumulation formula related to $Uex_{i,j}^{R}$, as shown in Formula (10).

$$ReT\left(Uex_{i,j}^{R}\right) = s_i * \sum_{j \in RPTS_i} \frac{e^{z*Uex_{i,j}^{R}} - e^{-z*Uex_{i,j}^{R}}}{e^{z*Uex_{i,j}^{R}} + e^{-z*Uex_{i,j}^{R}}} \tag{10}$$

where s_i is the reinforcement coefficient of the participant, indicating the degree of difficulty for the platform to cultivate the path-dependence of participant $\mathbb{u}_i$. The larger s_i is, the easier it is to cultivate, and the smaller s_i is, the more difficult it is to cultivate, with differences in each participant. $RFPC_i$ is the set of remote-area task rounds that participant $\mathbb{u}_i$ has completed at the current stage, excluding hot-area tasks completed by the participant. The completion of hot area tasks does not increase the dependency function value.z is the adjustment parameter,because

$$\frac{d\left(\frac{e^{z*Uex_{i,j}^{R}} - e^{-z*Uex_{i,j}^{R}}}{e^{z*Uex_{i,j}^{R}} + e^{-z*Uex_{i,j}^{R}}}\right)}{d\left(z*Uex_{i,j}^{ratep}\right)} = \frac{4}{\left(e^{z*Uex_{i,j}^{R}} + e^{-z*Uex_{i,j}^{R}}\right)^2} > 0,$$

$$\frac{d^2\left(\frac{e^{z*Uex_{i,j}^{R}} - e^{-z*Uex_{i,j}^{R}}}{e^{z*Uex_{i,j}^{R}} + e^{-z*Uex_{i,j}^{R}}}\right)}{d^2\left(z*Uex_{i,j}^{R}\right)} = -\frac{8e^{z*Uex_{i,j}^{R}} - e^{-z*Uex_{i,j}^{R}}}{\left(e^{z*Uex_{i,j}^{R}} + e^{-z*Uex_{i,j}^{R}}\right)^3} \leq 0,$$

Therefore, it increases monotonously with $Uex_{i,j}^{R}$ and the growth rate decreases gradually. z can make $z * Uex_{i,j}^{R}$ part enter the appropriate definition domain of function $\frac{e^{z*Uex_{i,j}^{R}} - e^{-z*Uex_{i,j}^{R}}}{e^{z*Uex_{i,j}^{R}} + e^{-z*Uex_{i,j}^{R}}}$, making its rising trend obvious; therefore, set $z < 1$. The definition field of $ReT\left(Uex_{i,j}^{R}\right)$ is $(0, +\infty)$, and the value field is $\left(0, n_i^{RT} * s_i\right)$. The platform quantifies the degree of path-dependence of the participants according to the change in their expected utility. According to Formula (10), the path-dependence function value of the participants is proportional to their expected utility. When $ReT\left(Uex_{i,j}^{R}\right)$ reaches the threshold value τ_i^{ReT}, the path-dependence cultivation of participants is completed. The specific analysis of the value of τ_i^{ReT} will be conducted in Section 4.3 Mechanism Evaluation.

The platform sets the calculation method for the path-dependence function as the qualification value of the participant's RAT. PCBL stipulates that participants' RAT qualification values accumulate above the threshold to enter the PM stage and take over tasks. According to Formula (10), RAT qualification value increases with the independent variable n_i^{RT}, which is a monotonically increasing function. Therefore, RAT qualification value increased with participants' continuous participation in RAT.

D. Participant selection algorithm

The setup of reward mechanism and $ReT\left(Uex_{i,j}^{R}\right)$ in Sections A and C of 4.1.2 guarantees that participants choose RAT, and the platform chooses participants through competitiveness function $T_{i,j}^{ta_m}(\cdot)$ in the following manner:

In Round j, participant $\mathbb{u}_i$ submits a quotation for the target task ta_m as $b_{i,j}^{ta_m}$. The participant's quotation is related to the cost $c_{i,j}^{ta_m}$ of participating in the task and its target profit $\mu_{i,j}^{ta_m}$, expressed as $b_{i,j}^{ta_m} = c_{i,j}^{ta_m} + \mu_{i,j}^{ta_m}$.

As mentioned in Section 3.1, whether participant $\mathbb{u}_i$ is the winner of the task competition is based on the bidding quotation of the participant and the distance between the participant and task. Therefore, a comprehensive score function $T_{i,j}^{ta_m}(\cdot)$ is defined to quantify after comprehensive consideration.

To motivate the participant to move to the task location while lowering the quotation, $T_{i,j}^{ta_m}(\cdot)$ should be negatively correlated with both $b_{i,j}^{ta_m}$ and $d_{i,j}^{ta_m}$, expressed as follows:

$$T_{i,j}^{ta_m}\left(b_{i,j}^{ta_m}, d_{i,j}^{ta_m}\right) = \frac{1}{\omega_1 * b_{i,j}^{ta_m} + \omega_2 * e^{\vartheta_{i,j}^{\widehat{ta}_m} * d_{i,j}^{ta_m}}} \tag{11}$$

where ω_1 and ω_2 are the score weights of absolute quotation value and moving distance, respectively, and have $\omega_1 + \omega_2 = 1$. $\vartheta_{i,j}^{\widehat{ta}_m}$ is the competitive cost factor with $\vartheta_{i,j}^{ta_m} < \vartheta_{i,j}^{\widehat{ta}_m}$. The overall scores of the participants competing for the same task were ranked, and the winner was the participant with the highest functional score.

Make the task selection weight $tw_{i,j}^{ta_m}$ to indicate the priority that the participant chooses when selecting a task. The detailed discussion is in Appendix C.

In summary, the overall PCBL process is shown in Algorithm 1, the PT stage algorithm (PTSA).

The input of Algorithm 1 is round J RAT participant set $\mathbb{u}_j^{RT}$, and the platform setting depends on the dependency reinforcement reward factor K_1. Round J selects the participants of RAT, and let the participants cumulative number of RATs plus 1 (line 1-2). The participants provide the platform with a prediction probability $ep_{i,j}$ (line 3), the platform calculates the value of the participant's $rex_{i,j}$ (line 4-9), and then calculates the participant's $ReT\left(Uex_{i,j}^{R}\right)$ (line 10-14). The calculated $ReT\left(Uex_{i,j}^{R}\right)$ and $ep_{i,j}$ are used as threshold judgments. When both reach the threshold, the participants exit the PT stage and enter the PM stage in the next round. Otherwise, the participant remains in the PT stage, updates its relevant parameters (line 15-20), calculates $rtr_{i,j}$ and issues an actual reward (line 21-24) to the participant.

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Algorithm 1: PT Stage Path Cultivation Algorithm,PTSA

Input : $\mathbb{u}_j^{RT} = \{\mathbb{u}_1^{RT}, \mathbb{u}_2^{RT}, \ldots, \mathbb{u}_N^{RT}\}$, K_1
Output: $Re_{i,j}^F$

for all $\mathbb{u}_i^{RT} \in \mathbb{u}_j^{RT}$ do
  $n_i^{RT} = n_i^{RT} + 1$;
  $ep_{i,j} \leftarrow$ Feedback prediction probability;
  $Pr_{i,j}$;
  $\varsigma_{i,j}$;
  $\mathbb{R}b_{i,j} = b_{i,j}^{ta_{m1}}$;
  $\mathbb{F}i_{i,j} \leftarrow$ Calculate the Fixed bonus;
  $\mathbb{D}r_{i,j} = K_1 * \frac{t_{i,j}}{\sqrt{2\pi}\sigma}$;
  $rex_{i,j} \leftarrow \{\mathbb{R}b_{i,j}, \varsigma_{i,j}, \mathbb{F}i_{i,j}, Pr_{i,j}, \mathbb{D}r_{i,j}\}$;
  $Uex_{i,j}^R = rex_{i,j} - c_{i,j}^{ta_m}$;
  $tw_{i,j}^{ta_m} = \frac{T_{i,j}^{ta_m}(\cdot) * Uex_{i,j}^R}{\rho_{ta_m,j}}$; Task selection weights
  $\max\left(tw_{i,j}^{ta_m}\right)$; Task selection
  $ReT\left(Uex_{i,j}^R\right)$;
  $Re_{i,j}^T \leftarrow ReT\left(Uex_{i,j}^R\right)$; Update the $Re_{i,j}^T$
  if $ReT\left(Uex_{i,j}^R\right) > \tau_i^{ReT}$ then

$$Pd\left(n_i^{RT}\right) = \sum_{n=1}^{n_i^{RT}} \frac{1}{\lambda_i + \log n} * \alpha_1 + \left(1 - \frac{1}{\lambda_i + \log n}\right) * \alpha_2$$

    if $ep_{i,j} > \beth * \alpha_{i,j}^r$ then
      u_i^{RT} Finishes the PT stage;
    end if
  end if
  $n_i^{ep} = n_i^{ep} + 1$;
  $\alpha_2 = \alpha_1 + \frac{n_i^{ep}}{n_i^{RT}}$; Update parameter;
  $\alpha_{i,j}^r = \frac{1}{K_i}$; Calculate the real probability;
  $rtr_{i,j} \leftarrow \left\{\mathbb{R}b_{i,j}, \varsigma_{i,j}, \mathbb{F}i_{i,j}, \alpha_{i,j}^r, \mathbb{D}r_{i,j}\right\}$;
end for
return $Re_{i,j}^T$

4.2 Path Maintenance Mechanism Based on Reference Effect

After the PT stage participants, $Pr_{i,j}$ and $ReT\left(Uex_{i,j}^R\right)$ reach the threshold and then enter the PM stage to receive tasks. The participant selection algorithm is the same as in the PT stage. In the PM stage, the platform sets up PMRE, prevents participants from quitting by setting dynamic and static double reference points, and maintains RAT selection by participants through the cognitive bias formed in the PT stage.

4.2.1 *Participant Reward Algorithm for PM Stage*

The PM stage platform must improve its utility while maintaining the task selection path of the participants. Therefore, when the participants initially enter the PM stage, they need to modify the probability incubation function and reward algorithm to improve platform utility through the change of probability incubation function while maintaining participants' path-dependence with the reward algorithm. After the $\mathbb{u}_i$ enters the PM stage, the platform counts the number of times that the $\mathbb{u}_i$ participates in the task in the PM stage. n_i^{RM} indicates the number of times $\mathbb{u}_i$ participates in RAT in the PM stage, n_i^{HM} indicates the number of times $\mathbb{u}_i$ participates in HAT in the PM stage, and n_i^{GDM} indicates the number of times $\mathbb{u}_i$ participates in RAT in the PM stage and obtains the $\mathbb{D}r_{i,j}^M$ dependent on the reinforcement. The platform announces to the participants that the probability of PM stage dependent on $\mathbb{D}r_{i,j}^M$ is to cultivate the probability value $Pr_{i,j}^M$ for PM stage, and the probability of actual issuance is $\widetilde{\alpha}_{i,j}^r$. The probability incubation function and reward algorithm under PMRE are described below.

A. PM stage probability cultivation function

In the PM stage, the platform completed the training of overestimated small probability of participants in the PT stage; therefore, $Pr_{i,j}^M$ was greater than the threshold. Therefore, in the PM stage, the probability weight formula of prospect theory was used to model participants' sensing of probability.The platform takes $Pr_{i,j}^M$ as the probability cultivation function for obtaining reinforcement reward at PM stage, thereby expanding the information gap between the platform and participants. $Pr_{i,j}^M$ modeling must ensure that the weight factor of posterior probability continues to increase as the number of participants participating in tasks in remote areas and obtaining additional reward n_i^{RM} increases. Therefore, $Pr_{i,j}^M$ of the platform setting PM stage is expressed as follows:

$$Pr_{i,j}^M = \begin{cases} \pi\left(\alpha_1\right) + \alpha_3, n_i^{RM} = 0 \\ \frac{1}{\lambda_i + \log\left(\mu_m * n_i^{RM} + 1\right)} * \left(\pi\left(\alpha_1\right) + \alpha_3\right) + \\ \left(1 - \frac{1}{\lambda_i + \log\left(\mu_m * n_i^{RM} + 1\right)}\right) * \frac{n_i^{GDM}}{n_i^{RM}}, n_i^{RM} > 0 \end{cases} \tag{12}$$

where α_3 is the initial compensation probability for PM stage and μ_m is the adjustment factor. To reduce the rate of $Pr_{i,j}^M$ changing with n_i^{RM}, $\mu_m \leq 1$ is set. $\frac{n_i^{GDM}}{n_i^{RM}}$ is the posterior probability of PM stage. To ensure the stability of the mechanism and reduce the randomness, it is the same as that set at Formula (3), with $\frac{n_i^{GDM}}{n_i^{RM}} \rightarrow \widetilde{\alpha}_{i,j}^r$. $\pi\left(\alpha_1\right)$ denotes a probability weight function and its specific expression is $\pi\left(\alpha_1\right) = \frac{{\alpha_1}^{\gamma}}{\left[{\alpha_1}^{\gamma} + (1-\alpha_1)^{1-\gamma}\right]^{\frac{1}{\gamma}}}$.

γ is a probability weight parameter indicating the degree to which participants are affected by PCBL in the PT stage to overestimate the probability. In the PT stage, jmax represents the final round, with $\gamma = \frac{ep_{i,jmax}}{Pr_{i,jmax}}$.

If the platform is going to recover costs in the PM stage to improve its own utility, it needs to make $\widetilde{\alpha}_{i,j}^r < \alpha_{i,j}^r$. Simultaneously, the platform sets a dynamic weighting factor to enlarge the information difference between the platform and the participants; therefore, $\widetilde{\alpha}_{i,j}^r$ is set as expressed:

$$\widetilde{\alpha}_{i,j}^r = e^{-n_i^{RM}} * \alpha_{i,j}^r + \left(1 - e^{-n_i^{RM}}\right) * \alpha_{i,j}^{min} \tag{13}$$

where $\alpha_{i,j}^{min}$ is the base probability that PM stage platform will grant participants dependent on dependency reinforcement reward. To make the platform more effective in the PM stage, $\alpha_{i,j}^{min} < \alpha_{i,j}^r$ is set up on the platform. Because of $n_i^{RM} \in N$, $e^{-n_i^{RM}}$ ranges from $(0, 1]$ and decreases monotonically with the increase in n_i^{RM}. According to Formula (13), the sum of weights $\alpha_{i,j}^r$ and $\alpha_{i,j}^{min}$ corresponding to $e^{-n_i^{RM}}$ and $1 - e^{-n_i^{RM}}$ is 1 and $\alpha_{i,j}^{min} < \alpha_{i,j}^r$, respectively; therefore, $\widetilde{\alpha}_{i,j}^r < \alpha_{i,j}^r$. Therefore, the platform in the PM stage can reduce costs and improve platform effectiveness.

In the PM stage, the platform announces the probability interval $I_{PM} = \left[\widetilde{\alpha}_{i,j}^r, Pr_{i,j}^M\right]$ to the participants, and the probability of all participants obtaining $\mathbb{D}r_{i,j}$ is the value in $\left[\widetilde{\alpha}_{i,j}^r, Pr_{i,j}^M\right]$. The participants in the PM have completed the

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probability overestimation cultivation, using the right interval of the probability interval as the expected probability.

B. PM Stage Reward Algorithmn

The expected reward $rex_{i,j}^{M}$ for participants in remote-area tasks in the PM stage is also composed of the basic task reward $\mathbb{R}b_{i,j}^{M}$, fixed reward $\mathbb{F}i_{i,j}^{M}$, and dependent reinforcement reward $\mathbb{D}r_{i,j}^{M}$, expressed as follows:

$$rex_{i,j}^{M} = \mathbb{R}b_{i,j}^{M} + \mathbb{F}i_{i,j}^{M} + Pr_{i,j}^{M} * \mathbb{D}r_{i,j}^{M} \tag{14}$$

Compared with PT stage, the basic task reward $\mathbb{R}b_{i,j}^{M}$ is no longer determined by the participant's bid price, but is obtained by the platform in combination with the participant's bid price and $Pr_{i,j}^{M}$ value, expressed as $\mathbb{R}b_{i,j}^{M} = Pr_{i,j}^{M} * b_{i,j}^{ta_m}$.

$\mathbb{F}i_{i,j}^{M}$ is determined by the fixed reward factor $\varsigma_{i,j}^{M}$ in the PM stage, the task qualification threshold τ_i^{ce} in remote areas, and the fixed reward $\Theta_{i,j}^{M}$ in base. By accumulating the number of times a participant participates in a remote area task during the PM stage, $\varsigma_{i,j}^{M}$ will increase and the utility will be compensated for. When the $\varsigma_{i,j}^{M}$ value of participant $\mathbb{u}_i$ is below the threshold τ_i^{ce}, the participant's remote area task qualification is insufficient, and RAT reward is affected. Therefore, the expression of $\mathbb{F}i_{i,j}^{M}$ is shown as $\mathbb{F}i_{i,j}^{M} = \left(\varsigma_{i,j}^{M} - \tau_i^{ce}\right) * \Theta_{i,j}^{M}$.

$\varsigma_{i,j}^{M}$ represents the factor by which participants receive a fixed reward after participating in remote area tasks. Participants are affected by PT cultivation during the PM stage; therefore, the setting of $\varsigma_{i,j}^{M}$ is related to PT stage related parameters. To motivate participants to participate in RAT, $\varsigma_{i,j}^{M}$ is positively related to n_i^{RM}, n_i^{HM}, and $t_{i,j}$; therefore, it is expressed as follows:

$$\varsigma_{i,j}^{M} = \frac{\varepsilon_i}{n_i^{RTT}} + \frac{\eta_1 * \eta_2 * e^{t_{i,j}*\left(n_i^{RM} - n_i^{HM}\right)}}{\eta_1 + \eta_2 * \left(e^{t_{i,j}*\left(n_i^{RM} - n_i^{HM}\right)} - 1\right)} \tag{15}$$

where ε_i represents the value of the $\mathbb{u}_i$ path-dependence function at the end of the PT stage. The average remote area task qualification value for each participant entering the PM stage was calculated and rewarded to the participant as the initial value of the fixed additional reward factor. n_i^{RTT} represents the total number of remote area tasks that $\mathbb{u}_i$ received during the PT stage. n_i^{HM} denotes the number of times $\mathbb{u}_i$ has received a mission in the PM stage for popular regions. η_1 and η_2 are two coefficients, and the platform sets $\eta_1 > \eta_2 > 0$. Formula (15) can be converted to $\varsigma_{i,j}^{M} = \frac{\varepsilon_i}{n_i^{RTT}} + \frac{\eta_1 * \eta_2}{\frac{\eta_1}{e^{t_{i,j}*\left(n_i^{RM} - n_i^{HM}\right)}} + \eta_2 * \left(1 - \frac{1}{e^{t_{i,j}*\left(n_i^{RM} - n_i^{HM}\right)}}\right)} = \frac{\varepsilon_i}{n_i^{RTT}} + \frac{\eta_1 * \eta_2}{\eta_2 + \frac{\eta_1 - \eta_2}{e^{t_{i,j}*\left(n_i^{RM} - n_i^{HM}\right)}}}$, $\eta_1 - \eta_2 > 0$, $\eta_1 * \eta_2 > 0$ and $e^{t_{i,j}*\left(n_i^{RM} - n_i^{HM}\right)} > 0$. From the aforementioned deduction, it can be concluded that participants completing remote area tasks in the PM stage will increase the value of $\varsigma_{i,j}^{M}$, completing the popular area tasks will decrease the value of $\varsigma_{i,j}^{M}$, and the $\varsigma_{i,j}^{M}$ value range will be $\left(\frac{\varepsilon_i}{n_i^{RTT}}, \frac{\varepsilon_i}{n_i^{RTT}} + \eta_1\right)$.

In the PM stage, because the platform has completed probability cultivation, participants are not required to submit the expected probability $ep_{i,j}$. Therefore, setting $\Theta_{i,j}^{M} = \frac{t_{i,j}}{\sqrt{2\pi}\sigma}$, the maximum value of $\Theta_{i,j}^{M}$ in the PT stage, increases the fixed reward of RAT and the expected reward of RAT by setting $t_{i,j}$.

The PM stage relies on the dependency reinforcement reward $\mathbb{D}r_{i,j}^{M}$ expression, as shown in Formula (16).

$$\mathbb{D}r_{i,j}^{M} = \int_{\rho_{ta_{mi},j}}^{\max\left(\rho_{ta_{m1},j}, \rho_{ta_{m2},j}, \dots \rho_{ta_{mM},j}\right)} K_2 * \frac{t_{i,j}}{\sqrt{2\pi}\sigma} d\rho \tag{16}$$

$$\text{where } t_{i,j} = \frac{\min\left(\rho_{ta_{m1},j}, \rho_{ta_{m2},j}, \dots \rho_{ta_{mM},j}\right)}{\rho_{ta_{mi},j}}$$

K_2 indicates that the PM stage relies on the dependency reinforcement reward factor. Because participants in the PM stage have an overestimated probability and the platform needs to improve its effectiveness, the platform sets up $K_2 < K_1$. Because of $K_2 * \frac{t_{i,j}}{\sqrt{2\pi}\sigma} > 0$, $\mathbb{D}r_{i,j}^{M}$ is negatively correlated with $\rho_{ta_{mi},j}$.

According to Formula (13), in the PM stage, the platform needs to reduce the reward to improve the platform's effectiveness; therefore, the probability of actual $\mathbb{D}r_{i,j}^{M}$ is lower than the cultivation probability value $Pr_{i,j}^{M}$ published in the PM stage, and the participant's actual reward $rtr_{i,j}^{M}$ is expressed as follows:

$$rtr_{i,j}^{M} = \mathbb{R}b_{i,j}^{M} + \mathbb{F}i_{i,j}^{M} + \widetilde{\alpha}_{i,j}^{r} * \mathbb{D}r_{i,j}^{M} \tag{17}$$

Expected utility $Uex_{i,j}^{RM}$ calculation for PM stage participants, expressed as $Uex_{i,j}^{RM} = rtr_{i,j}^{M} - C_{i,j}^{ta_m}$.

This section presents the probability function and reward algorithm of the PM stage. It improves the actual utility of the platform by setting the probability function and real probability and reduces the speed of the decline in the expected utility of participants by combining the probability function and reward algorithm. This approach forms an initial maintenance for participants. To further improve the retention rate of participants and ensure their long-term participation, an exit tax algorithm based on double reference points is proposed in Section 4.2.2.

4.2.2 PM Stage Exit Tax Algorithm Based on Double Reference Points

This section sets up the dynamic and static reference points for $Pu_{i,j}^{PM}$ to maintain the long-term participation of participants without additional costs. Static reference points provide participants with a static target for the final zero exit tax. Dynamic reference points provide participants with a dynamic target for each round of the process. They work together to ensure that participants do not quit the task until the $ReM\left(Uex_{i,j}^{RM}\right)$ drops to the threshold τ_i^{ReM}, in addition to improving the retention rate of participants.

A. PM Stage Static Reference Point Settings

Static reference points were set using $ReM\left(Uex_{i,j}^{RM}\right)$, which is a PM stage participant path-dependence function with the same meaning as the PT stage.

In the PM stage, participants were nurtured during the PT stage, and according to PCBL, the initial value of the participant's $ReM\left(Uex_{i,j}^{RM}\right)$ is influenced by the value of $ReT\left(Uex_{i,j}^{R}\right)$ at the end of the PT stage. In the PM stage, the platform maintains the path formed by the participant's PT stage. After the training of PSTA algorithm to overestimate the small probability and path-dependence of participants, participants who just entered the PM stage have higher $Pr_{i,j}$ and $ReT\left(Uex_{i,j}^{R}\right)$ values and higher expected utility of RAT. As the number of rounds of participants participating in the PM stage increases, the nurturing probability decreases and the effectiveness of participants decreases. Therefore, setting $ReM\left(Uex_{i,j}^{RM}\right)$ is expressed as follows:

$$ReM\left(Uex_{i,j}^{RM}\right) = \varphi_i * \varepsilon_i + s_i * \sum_{j \in RPMS_i} \frac{e^{\triangle U_{i,j}} - e^{-\triangle U_{i,j}}}{e^{\triangle U_{i,j}} + e^{-\triangle U_{i,j}}} \quad (18)$$

where ε_i represents the value of the $\mathbb{u}_i$ path-dependence function at the end of PT stage, φ_i denotes the initial coefficient of the path-dependence function after $\mathbb{u}_i$ enters PM stage, and n_i^{RTT} indicates the number of times $\mathbb{u}_i$ participates in RAT during PT stage. According to the PTSA algorithm, $\varphi_i = \log n_i^{RTT}$ is set because the path-dependence incubation effect obtained by participants on PT stage affects the PM stage. The expression of φ_i shows that the value of φ_i is related to n_i^{RTT}, and with the increase in n_i^{RTT}, the initial value coefficient increases. $RPMS_i$ represents the collection of RATs that the $\mathbb{u}_i$ participates in during the PM stage. $\triangle U_{i,j}$ denotes relative utility, which is the relative value between the utility of the participant's PM stage and that of the PT stage, expressed as $\triangle U_{i,j} = Uex_{i,j}^{RM} - Uex_{i,jmax}^{R}$, and $Uex_{i,jmax}^{R}$ denotes the expected utility of the participant's last participation in RAT. The platform sets the average utility threshold of participants in the PT stage as the expected utility threshold in the PM stage. Formula (18) shows that a lower utility can negatively affect the path-dependence function and reduce the path-dependence value of participants compared to the PT stage.

Static reference points guarantee that participants will continue to participate with a threshold τ_i^{ReM} and a reference point of zero exit tax. However, only the dynamic reference point participants have more rounds to reach their goals. In each round of tasks, dynamic reference points need to be added to form a dynamic goal for each round to ensure that participants do not quit the task before the $ReM\left(Uex_{i,j}^{RM}\right)$ drops to the threshold τ_i^{ReM}, in addition to preventing further reduction in the participants' early exit.

B. PM Stage Dynamic Reference Point Settings

Dynamic reference points were formed by setting $Pu_{i,j}^{PM}$. For participants who exit the PM stage, the platform deducts part of their reward as a tax for those who exit the PM stage.

Because a reference point for $Pu_{i,j}^{PM}$ is to be formed in the exit tax deduction rules, the setting of $Pu_{i,j}^{PM}$ needs to be negatively related to n_i^{RM}, and $Pu_{i,j}^{PM}$ should be related to the cumulative extra reward in previous rounds to ensure the continuous participation of participants, expressed as follows:

$$Pu_{i,j}^{PM} = Pr_{i,j}^{M} * \left(\frac{\sum_{j \in RPMS_i} \Theta_{i,j}^{M} + \sum_{j \in RPMS_i^{g}} \mathbb{D}r_{i,j}^{M}}{n_i^{RM}} + \mu_{i,j}\right) \quad (19)$$

Formula (19) shows that $Pu_{i,j}^{PM}$ is related to the cultivation probability $Pr_{i,j}^{M}$ in the PM stage and the average extra reward that $\mathbb{u}_i$ has earned so far. $RPMS_i$ represents the set of RATs for participants in the PM stage and $RPMS_i^{g}$ represents the set of tasks for which $\mathbb{u}_i$ participates in RATs in the PM stage and receives the dependent reinforcement reward.

$$tax_{i,j} = \begin{cases} Pu_{i,j-1}^{PM} + \varpi * \left(Pu_{i,j-1}^{PM} - Pu_{i,j}^{PM}\right)^{\beta}, \\ \quad \text{if } ReM(Uex_{i,j}^{RM}) > \tau_i^{ReM} \,\&\&\, Pu_{i,j-1}^{PM} > Pu_{i,j}^{PM} \\ Pu_{i,j-1}^{PM}, \\ \quad \text{if } ReM(Uex_{i,j}^{RM}) > \tau_i^{ReM} \,\&\&\, Pu_{i,j-1}^{PM} \le Pu_{i,j}^{PM} \\ 0, \text{if} ReM(Uex_{i,j}^{RM}) \le \tau_i^{ReM} \end{cases} \quad (20)$$

The platform sets the exit tax deduction rules as follows, the total exit tax is $tax_{i,j}$, and τ_i^{ReM} represents the threshold of the participant $ReM\left(Uex_{i,j}^{RM}\right)$. When $\mathbb{u}_i$ exits the task, if $ReM\left(Uex_{i,j}^{RM}\right) >= \tau_i^{ReM}$, the platform calculates the participant's j-1 exit tax $Pu_{i,j-1}^{PM}$ and j exit tax $Pu_{i,j}^{PM}$. If this exit round is selected, the platform deducts the j-1 exit tax $Pu_{i,j-1}^{PM}$, and if the next exit round is selected, the platform deducts the jth exit tax $Pu_{i,j}^{PM}$. For each exit round, if $Pu_{i,j-1}^{PM} > Pu_{i,j}^{PM}$, the $\varpi * \left(Pu_{i,j-1}^{PM} - Pu_{i,j}^{PM}\right)^{\beta}$'s tax is deducted, that is $tax_{i,j} = Pu_{i,j-1}^{PM} + \varpi * \left(Pu_{i,j-1}^{PM} - Pu_{i,j}^{PM}\right)^{\beta}$, where $tax_{i,j} = Pu_{i,j-1}^{PM} + \varpi * \left(Pu_{i,j-1}^{PM} - Pu_{i,j}^{PM}\right)^{\beta}$,$\beta < 1$; if $ReM\left(Uex_{i,j}^{RM}\right) < \tau_i^{ReM}$, the platform will no longer deduct the exit tax, which is $tax_{i,j} = 0$.

According to the tax deduction rules, the exit tax base value of $\mathbb{u}_i$ in each round is compared with the exit tax base value in the next round, that is, the exit tax base value in the next round is a dynamic reference point. Simultaneously, when $ReM\left(Uex_{i,j}^{RM}\right) < \tau_i^{ReM}$, $tax_{i,j} = 0$, participants can exit without cost, which is the static reference point. This formed a double reference point. Establishing dynamic reference points requires the support of $Pu_{i,j}^{PM}$ related properties. The relationship between base tax $Pu_{i,j}^{PM}$ and the number of times $\mathbb{u}_i$ participates in the task is discussed in Theorem 3.

Theorem 3. If $ReM\left(Uex_{i,j}^{RM}\right) >= \tau_i^{ReM}$, the exit tax $Pu_{i,j-1}^{PM}$ chosen by the participant to quit the task is negatively correlated with the number of rounds n_i^{RM} to complete the task.

Proof: The proof of Theorem 3 is in Appendix D. □

Theorem 3 shows that $Pu_{i,j-1}^{PM} > Pu_{i,j}^{PM}$, that is, long-term participation of participants decreases the value of $Pu_{i,j}^{PM}$.The platform publishes the next round of exit tax $Pu_{i,j}^{PM}$ as a reference point for the participants. If a participant opts out in this round, the actual negative effect from the exit tax will be $-Pu_{i,j-1}^{PM}$. If they opt out in the next round, the actual negative effect of the exit tax is $-Pu_{i,j}^{PM}$. If they opt out in the next round, the actual negative effect will be expanded to $-Pu_{i,j-1}^{PM} - \varpi * \left(Pu_{i,j-1}^{PM} - Pu_{i,j}^{PM}\right)^{\beta}$ according to the tax deduction rules set up by the platform and Theorem 3. Each reference point will change to the next exit tax and negative utility will exist in each round.

As the task progresses, n_i^{RM} increases and $ReM\left(Uex_{i,j}^{RM}\right)$ negatively correlates with n_i^{RM}; therefore, $ReM\left(Uex_{i,j}^{RM}\right)$ decreases and approaches the static reference point τ_i^{ReM}. When $ReM\left(Uex_{i,j}^{RM}\right) < \tau_i^{ReM}$ occurs, participants can exit the platform without cost, and the negative effect of tax is zero; therefore, participants will continue to participate in the task. The dynamic and static reference points work together to prevent the participants from quitting the task ahead of time.

In summary, the overall flow of PMRE in the PM stage is shown in Algorithm 2, reference effect maintenance algorithm (ERMA).

The input to Algorithm 2 is the participant set $\mathbb{u}_j^{RM}$ in the jth round of the PM stage and the output is the updated participant set $\mathbb{u}_{j+1}^{RM}$ in the next round. For each participant in

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Algorithm 2: Reference Effect Maintenance Algorithm ERMA

Input : $\mathbb{u}_j^{RM} = \{\mathbb{u}_1^{RM}, \mathbb{u}_2^{RM}, \ldots, \mathbb{u}_N^{RM}\}$
Output: $\mathbb{u}_{j+1}^{RM}$

1 $\mathbb{u}_{j+1}^{RM} \leftarrow \emptyset$;
2 for all $\mathbb{u}_i^{RM} \in \mathbb{u}_j^{RM}$ do
3 $\quad rex_{i,j}^M \leftarrow \left\{\mathbb{R}b_{i,j}^M, \varsigma_{i,j}^M, \mathbb{F}i_{i,j}^M, Pr_{i,j}^M, \mathbb{D}r_{i,j}^M\right\}$;
4 $\quad Uex_{i,j}^{RM} = rex_{i,j}^M - c_{i,j}^{ta_m}$;
5 $\quad ReM\left(Uex_{i,j}^{RM}\right)$;
6 $\quad Pr_{i,j}^M$;
7 $\quad \widetilde{\alpha}_{i,j}^r$; Calculate the Real probability
8 $\quad Pu_{i,j-1}^{PM}$, $Pu_{i,j}^{PM}$;Calculate the Base tax
9 $\quad$ if $\mathbb{u}_i^{RM}$ exit task then
10 $\quad\quad$ if $ReM\left(Uex_{i,j}^{RM}\right) \geq \tau_i^{ReM}$ then
11 $\quad\quad\quad$ if $Pu_{i,j-1}^{PM} > Pu_{i,j}^{PM}$ then
12 $\quad\quad\quad\quad tax_{i,j} = Pu_{i,j-1}^{PM} + \varpi * \left(Pu_{i,j-1}^{PM} - Pu_{i,j}^{PM}\right)^\beta$;
13 $\quad\quad\quad$ else
14 $\quad\quad\quad\quad tax_{i,j} = Pu_{i,j-1}^{PM}$;
15 $\quad\quad\quad$ end if
16 $\quad\quad$ else if $ReM\left(Uex_{i,j}^{RM}\right) < \tau_i^{ReM}$ then
17 $\quad\quad\quad tax_{i,j} = 0$;
18 $\quad\quad$ end if
19 $\quad\quad \mathbb{u}_i^{RM}$ exit PM;
20 $\quad\quad$ Remove $\mathbb{u}_i^{RM}$ from $\mathbb{u}_j^{RM}$;
21 $\quad$ end if
22 end for
23 $\mathbb{u}_{j+1}^{RM} \leftarrow \mathbb{u}_j^{RM}$;
24 return $\mathbb{u}_{j+1}^{RM}$

the $\mathbb{u}_j^{RM}$, first empty the $\mathbb{u}_{j+1}^{RM}$ (line 1), calculate the current reward $rex_{i,j}^M$ and utility $Uex_{i,j}^{RM}$ (line 3-4), and further calculate the $ReM\left(Uex_{i,j}^{RM}\right)$, $Pr_{i,j}^M$, $\widetilde{\alpha}_{i,j}^r$, $Pu_{i,j-1}^{PM}$, and other parameters (line 5-7) of the participant. When a participant exits the task, a high $tax_{i,j}$ (line 8-11) is deducted if the participant satisfies the $ReM\left(Uex_{i,j}^{RM}\right) < \tau_i^{ReM}$ and $Pu_{i,j-1}^{PM} > Pu_{i,j}^{PM}$, a lower $tax_{i,j}$ (line 12-13) is deducted if the participant satisfies $ReM\left(Uex_{i,j}^{RM}\right) < \tau_i^{ReM}$ and $Pu_{i,j-1}^{PM} \leq Pu_{i,j}^{PM}$, and no tax (line 14-17) is deducted if the participant satisfies DSDS. The participant exiting the task is removed from the $\mathbb{u}_j^{RM}$ (line 18-20) and a $\mathbb{u}_{j+1}^{RM}$ (line 22) is obtained.

The expected utility of the participant in the exit case is expressed as follows:

$$Uqu_{i,j} = rex_{i,j}^M - c_{i,j}^{ta_m} - \left(Pu_{i,j-1}^{PM} + \varpi * \left(Pu_{i,j-1}^{PM} - Pu_{i,j}^{PM}\right)^\beta\right) \tag{21}$$

Various incentive mechanism algorithm studies in LDMC have demonstrated that if a participant quits halfway and causes its own negative effects, it can effectively prevent the participant from quitting. The following discusses the effect of a participant's withdrawal on their utility through Theorem 4.

Theorem 4. If $ReM\left(Uex_{i,j}^{RM}\right) >= \tau_i^{ReM}$ exits the participant, then the utility value of this round $Uqu_{i,j}$ is negative, that is, $Uqu_{i,j} < 0$.

Proof: The proof of Theorem 4 is in Appendix E. □

Theorem 4 shows that a participant quitting halfway through results in a negative utility round. The discussion regarding Theorem 4 is in Appendix F.

Platforms increase utility during the PM stage, which reduces the real probability that participants will receive additional reward; therefore, the $ReM\left(Uex_{i,j}^{RM}\right)$ of the participant's path-dependence function value decreases after multiple participation in the task. According to the ERMA and Theorem 4, the participants' choice of this round of exit tasks under the influence of PMRE has a negative effect, making the total utility of this round negative; therefore, the participants will choose to complete the PM stage tasks. Participants choose to perform more tasks to reduce taxes when considering quitting a task, and the platform maintains long-term participation by setting a quitting tax.

4.3 Mechanism Assessment

This section discusses the parametric nature of TCPD and evaluates incentive performance. Utility and task coverage are two important parameters of LDMC. Most incentive mechanisms currently focus on improving these two parameters; therefore, this section mainly evaluates them.

4.3.1 Mechanism Utility Assessment

The platform and participant utilities are discussed below. Platform utility involves variables such as task value and platform cost. First, related concepts are presented.

A. Property Analysis of Important Variables

The task value $v_{ta_m,j}$ is the value that HAT ta_m presents to the platform after completing the jth round. $v_{ta_m,j}$ is determined by the participant density $\rho_{ta_m,j}$ near the task location. The smaller the participant density, the more difficult is the task location data collection, and the higher is the value of the task to the platform, which is expressed as follows:

$$v_{ta_m,j} = c_{ta_m,j}^{\text{data}} + e^{\vartheta_{ta_m,j} * \frac{1}{\rho_{ta_m,j}}} - 1 \tag{22}$$

Set task ta_{m1} as RAT, ta_{m2} as HAT, then $\rho_{ta_{m1},j} < \rho_{ta_{m2},j}$. The platform determines its relationship according to its own utility. The platform's cost Cpt_i for $\mathbb{u}_i$ is the part of the platform that deducts the tax $tax_{i,j}$ from the reward paid to $\mathbb{u}_i$. The calculation method is expressed as follows:

$$Cpt_i = \sum_{j \in RPTS} rtr_{i,j} + \sum_{j \in RPMS} rtr_{i,j}^M - \sum_{j \in RPMS} tax_{i,j} + \sum_{j \in HAT} \mathbb{H}b_{i,j} \tag{23}$$

The total platform utility for all tasks submitted by a $\mathbb{u}_i$ is Upu_i. The difference between the task value generated by the way $\mathbb{u}_i$ accomplishes the task and the platform cost Cpt_i is expressed as follows:

$$Upu_i = \sum_{R_m \in RAT} v_{ta_{m1},j} + \sum_{H_m \in HAT} v_{ta_{m2},j} - Cpt_i \tag{24}$$

The nature of the expected utility of participants throughout the process is discussed below.

In the PT stage, there is $ReT\left(Uex_{i,j}^R\right) < \tau_i^{ReT}$, and $Uex_{i,j}^R = rex_{i,j} - c_{i,j}^{ta_{m1}}$. Based on Section 4.1.2A Formulas (4) and (5), $Uex_{i,j}^R = \mathbb{R}b_{i,j} + \varsigma_{i,j} * \Theta_{i,j} + Pr_{i,j} * \mathbb{D}r_{i,j} - c_{i,j}^{ta_{m1}}$ can be

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inferred by substituting $Uex_{i,j}^{R}$ of expected reward for PT stage participants, and $\alpha_{i,j}^{r} > Pr_{i,j}$. Therefore, the posterior probability $\frac{n_i^{GDT}}{n_i^{RT}} > \alpha_1$. According to Theorem 1, as the task progresses, participants gradually overestimate the probability. Moreover, according to Formula (3), $Pr_{i,j}$ is positively correlated with posterior probability; therefore, $Pr_{i,j}$ is positively correlated with n_i^{RT}, and according to the related deductions in Formulas (4), (5), and (7) in Section 4.1.1, $\varsigma_{i,j}$ is positively correlated with n_i^{RT}, while $\Theta_{i,j}$ is related to participant's decision-making, which is relatively stable; therefore, $Uex_{i,j}^{R}$ increases with the increase of n_i^{RT}.

In the PM stage, $ReT\left(Uex_{i,j}^{R}\right) > \tau_i^{ReT}$ and $ReM\left(Uex_{i,j}^{RM}\right) < \tau_i^{ReM}$ and $Uex_{i,j}^{RM} = rex_{i,j}^{M} - c_{i,j}^{ta_{m1}}$. According to Formulas (14), (15), and (16), the expected reward $rex_{i,j}^{M}$ of PM stage participants is substituted to obtain $Uex_{i,j}^{RM} = \mathbb{R}b_{i,j}^{M} + \left(\varsigma_{i,j}^{M} - \tau_i^{ce}\right) * \Theta_{i,j}^{M} + Pr_{i,j}^{M} * \mathbb{D}r_{i,j}^{M} - c_{i,j}^{ta_{m1}}$. According to Formulas (12) and (13), $\widetilde{\alpha}_{i,j}^{r} < \alpha_{i,j}^{r} < Pr_{i,j}^{M}$, $\frac{n_i^{GDT}}{n_i^{RT}} < \pi(\alpha_3)$ and $Pr_{i,j}^{M}$ is negatively related to n_i^{RM}, whereas $\Theta_{i,j}^{M}$ is related to participant decision making, which decreases first and then is relatively stable; therefore, $Uex_{i,j}^{RM}$ decreases with the increase in n_i^{RM}.

$\pi(\alpha_3) > \frac{n_i^{GDT}}{n_i^{RT}}$ can be obtained from Formula (12) when the participant has just moved from PT to PM, and $Uex_{i,1}^{RM} > Uex_{i,jmax}^{R}$ can be deduced further. Subsequently, owing to the decrease in $\widetilde{\alpha}_{i,j}^{r}$, $Pr_{i,j}^{M}$ decreases.

The nature of participants' real utility throughout the process is discussed below.

The real utility of PT stage participants is $Utr_{i,j}^{R} = rtr_{i,j} - c_{i,j}^{ta_{m1}}$, that is, the participant's real reward $rtr_{i,j}$ minus the participant's cost $c_{i,j}$. $rtr_{i,j} = \mathbb{R}b_{i,j} + \varsigma_{i,j} * \Theta_{i,j} + \alpha_{i,j}^{r} * \mathbb{D}r_{i,j}$ can be obtained by substituting Formulas (5) and (7) into Formula (8). So we can obtain $Utr_{i,j}^{R} = \mathbb{R}b_{i,j} + \varsigma_{i,j} * \Theta_{i,j} + \alpha_{i,j}^{r} * \mathbb{D}r_{i,j} - c_{i,j}^{ta_{m1}}$. Because $\alpha_{i,j}^{r} = K_1$ is a constant and $1 < \varsigma_{i,j} < e^{2t_i}$, $Utr_{i,j}^{R}$ is stable as a whole and does not fluctuate significantly with n_i^{RT}.

In the PM stage, participants' real utility $Utr_{i,j}^{RM} = rtr_{i,j}^{M} - c_{i,j}^{ta_{m1}}$, $rtr_{i,j}^{M} = \mathbb{R}b_{i,j}^{M} + \left(\varsigma_{i,j}^{M} - \tau_i^{ce}\right) * \Theta_{i,j}^{M} + \widetilde{\alpha}_{i,j}^{r} * \mathbb{D}r_{i,j}^{M}$ can also be obtained by substituting Section 4.2.1 Formulas (15) and (16) into Formula (17). $Utr_{i,j}^{RM} = \mathbb{R}b_{i,j}^{M} + \left(\varsigma_{i,j}^{M} - \tau_i^{ce}\right) * \Theta_{i,j}^{M} + \widetilde{\alpha}_{i,j} * \mathbb{D}r_{i,j}^{M} - c_{i,j}^{ta_{m1}}$ can be obtained by substituting the results into $Uex_{i,j}^{RM} = rtr_{i,j}^{M} - c_{i,j}^{ta_m}$, and $\widetilde{\alpha}_{i,j}^{r} = e^{-n_i^{RP}} * \alpha_{i,j}^{r} + \left(1 - e^{-n_i^{RP}}\right) * \alpha_{i,j}^{min}$, $\alpha_{i,j}^{r} > \alpha_{i,j}^{min}$. As participants participate in tasks more often, $\widetilde{\alpha}_{i,j}^{r}$ decreases and $\varsigma_{i,j}^{M} < \frac{\varepsilon_i}{n_i^{RTT}} + \eta_1$ has less influence; therefore, $Utr_{i,j}^{RM}$ is negatively correlated with n_i^{RM}.

Section 4.3.1A analyzes the properties of the important variables in TCPD, including their changing rules and size comparison, which lays a good foundation for the previous deduction of related theorems. The theorems related to the TC mechanism are presented in subsection B, and a mathematical proof is provided.

B. Theorem and Proof of Utility

Task ta_{m1} was set as RAT, ta_{m2} as HAT, and the individual task platform utility is $Ups_{i,j}^{R}$ when the participants selected RAT and $Ups_{i,j}^{H}$ when they selected HAT. The specific relationship between $\rho_{ta_{m1},j}$ and $\rho_{ta_{m2},j}$ is discussed below in Theorem 5.

Theorem 5. In TCPD, if $e^{\vartheta_{ta_{m1},j} * \frac{1}{\rho_{ta_{m1},j}}} - \left(\alpha_{i,j}^{r} * K_1\left(\max\left(\rho_{ta_{m1},j}, \rho_{ta_{m2},j}, \ldots \rho_{ta_{mM},j}\right) - \rho_{ta_{m1},j}\right) + 2\right) * b_{i,j}^{ta_{m1}} > e^{\vartheta_{ta_{m2},j} * \frac{1}{\rho_{ta_{m2},j}}}$, then $Ups_{i,j}^{R} > Ups_{i,j}^{H} > 0$ is guaranteed.

Proof: The proof of Theorem 5 is in Appendix G. □

Theorem 5 shows that when $\vartheta_{ta_{m1},j}$, $\rho_{ta_{m1},j}$, $\vartheta_{ta_{m2},j}$, and $\rho_{ta_{m2},j}$ meet the criteria, the platform utility is positive regardless of task type chosen by the participant, and RAT platform selected by the participant is more effective. Therefore, when $\rho_{ta_{m1},j}$ and $\rho_{ta_{m2},j}$ satisfy the condition of Theorem 5, the more RAT selected by participants in the whole task process, the higher the utility of the platform.

Further, the critical point of the transition between the PT and PM is discussed in Theorem 6. Create platform budget Bu_i for participant $\mathbb{u}_i$.

Theorem 6. There are unique PT and PM stage transition thresholds τ_i^{ReT} and τ_i^{pr} to maximize the utility of the platform.

Proof: The proof of Theorem 6 is in Appendix H. □

Theorem 6 shows that the platform utility can be maximized in TCPD, and the established τ_i^{ReT} and τ_i^{pr} exist and are unique. τ_i^{ReT} and τ_i^{pr} can be further solved. From Theorem 6, the conditions between the PT and PM stages are converted to those shown in Formula (25).

$$\begin{aligned}
&\max\left(\sum_{j\in RPTS} rtr_{i,j} + \sum_{j\in RPMS} rtr_{i,j}^{M} + \sum_{j\in HAT} \mathbb{H}b_{i,j}\right)\\
&\text{s.t.} \sum_{j\in RPTS} rtr_{i,j} + \sum_{j\in RPMS} rtr_{i,j}^{M} + \sum_{j\in HAT} \mathbb{H}b_{i,j} \le Bu_i \\
&\qquad Pd\left(n_i^{RT}\right) > \tau_i^{pr}
\end{aligned} \tag{25}$$

If the number of times a participant participates in a RAT in the PT stage is n_i^{RRT}, when the requirement is met, is $\tau_i^{ReT} = s_i * \sum_{n_i^{RT}=1}^{n_i^{RRT}} \frac{e^{z*Uex_{i,j}^{R}} - e^{-z*Uex_{i,j}^{R}}}{e^{z*Uex_{i,j}^{R}} + e^{-z*Uex_{i,j}^{R}}}$.

Next, we discuss the threshold τ_i^{ReM} that the PM stage allows participants to exit without deducting their reward. In the PM stage, when $ReM\left(Uex_{i,j}^{RM}\right) > \tau_i^{ReM}$, the exit from the PM stage, according to Theorem 4, will result in negative effects; therefore, participants will not choose to exit. When participants' expected rewards from RATs are less than those from HATs, participants will not choose RATs and the path-dependence effect will be relieved. In the PM stage, the expected utility of RAT is $Uex_{i,j}^{RM} = rex_{i,j}^{M} - c_{i,j}^{ta_{m1}}$. By substituting the expression $b_{i,j}^{ta_m} = c_{i,j}^{ta_m} + \mu_{i,j}^{ta_m}$ and Formula (14) in Section 4.2.1B, $Uex_{i,j}^{RM} = Pr_{i,j}^{M} * \mu_{i,j}^{ta_{m1}} - \left(1 - Pr_{i,j}^{M}\right) * c_{i,j}^{ta_{m1}} + \left(\varsigma_{i,j}^{M} - \tau_i^{ce}\right) * \Theta_{i,j}^{M} + Pr_{i,j}^{M} * \mathbb{D}r_{i,j}^{M}$ can be obtained. The expected utility of HAT is $Uex_{i,j}^{H} = \mathbb{H}b_{i,j} - c_{i,j}^{ta_{m2}}$, that is, $Uex_{i,j}^{H} = \mu_{i,j}^{ta_{m2}}$. According to Formula (12), $Pr_{i,j}^{M}$ decreases with the increase in n_i^{RM}; therefore, $Uex_{i,j}^{RM}$ decreases with the increase in n_i^{RM}. When $Uex_{i,j}^{RM} = Uex_{i,j}^{H}$ is the critical value and $Pr_{i,j}^{M} * \mu_{i,j}^{ta_{m1}} - \left(1 - Pr_{i,j}^{M}\right) * c_{i,j}^{ta_{m1}} + \left(\varsigma_{i,j}^{M} - \tau_i^{ce}\right) * \Theta_{i,j}^{M} + Pr_{i,j}^{M} * \mathbb{D}r_{i,j}^{M} = \mu_{i,j}^{ta_{m2}}$ occurs, if the number of participants participating in RATs in the PM stage is n_i^{RRM}, then $\tau_i^{ReM} = \varphi_i * \varepsilon_i + s_i * \sum_{n_i^{RM}=1}^{n_i^{RRM}} \frac{e^{\triangle U_{i,j}} - e^{-\triangle U_{i,j}}}{e^{\triangle U_{i,j}} + e^{-\triangle U_{i,j}}}$.

According to Theorem 5, when the participant chooses RAT, the platform is more effective in one round when the participant is in the PM stage. Therefore, once the participants meet the training threshold, they should enter the PM stage immediately to improve the platform's effectiveness.

Section 4.3.1 identifies and evaluates the nature and utility of platform and participant utilities, indicating that participants in

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the PT stage will be overestimated under the influence of high efficiency and poor information; in the PM stage; the platform will improve its utility and continue to use the information gap to change participants' expected utility to maintain it.

4.3.2 Task Coverage Assessment

This section evaluates and discusses task assignments and participant mobility. To attract participants to participate in RAT during the PT stage, PCBL is required to make the expected RAT of the participants to be more effective than the expected HAT. The expected utility of participants in RATs and HATs under PCBL is analyzed using Theorem 7.

Theorem 7. Participants' expected utility of RAT under PCBL during PT stage $Uex_{i,j}^{R}$ is higher than that of HAT $Uex_{i,j}^{H}$; that is, $\forall j$, $Uex_{i,j}^{R} > Uex_{i,j}^{H}$.

Proof: The proof of Theorem 7 is in Appendix I. □

Theorem 7 shows that participants participate in RATs more effectively than expected during the PT; therefore, participants will try to select RATs and increase their participation rate.

Initially, the participants were clustered in popular areas and were unevenly distributed. The task locations were distributed according to the data collection requirements. Typically, platforms require comprehensive data; therefore, they present a relatively even distribution. If the movement of the participants follows the distribution of task location, it will help improve the coverage of task completion and ensure data collection stability.

The interaction between the reward mechanism and $T_{i,j}^{ta_m}(\cdot)$ promotes the movement of participants to remote task location, which makes the distribution of participants change with the distribution of task location. Theorem 7 shows that $Uex_{i,j}^{R} > Uex_{i,j}^{H}$ in PCBL; that is, participants have higher expected utility for RAT; therefore, participants compete for RAT based on $T_{i,j}^{ta_m}(\cdot)$. From the mathematical nature of $T_{i,j}^{ta_m}(\cdot)$, $T_{i,j}^{ta_m}(\cdot)$ can reduce the distance $d_{i,j}^{ta_m}$ between the participants and task location. Reducing the distance between themselves and RAT points before task bidding begins is beneficial for winning a task competition. Therefore, $T_{i,j}^{ta_m}(\cdot)$ can promote more participants to move to RAT area and make the distribution of participants change with the distribution of task location.

Section 4.3.2 evaluates the effectiveness of task coverage. In PCBL, participants move to RAT because of $T_{i,j}^{ta_m}(\cdot)$ and task utility. As the task progressed, more participants were distributed around RAT, increasing the density of participants in remote areas and effectively improving the coverage rate for completing RAT.

5 SIMULATIONS AND EVALUATIONS

This section presents simulation experiments on TCPD to verify its effect. The simulation experiment used IntelliJ IDEA programming. This section compares TCPD with the DA-based [41] and on-demand [9] mechanisms. Both DA-based and on-demand are the top publication mechanisms in LDMC. They have the same physical background and incentive parameters as TCPD and are also representative of high-level papers in the field of MCS. Therefore, these two articles are selected for comparison, and the traditional reverse auction is included as a reference. DA-based is suitable for large-scale space-time data collection scenarios, and the on-demand mechanism has high complexity, low efficiency, and accuracy in high-load scenarios, and good performance in low-load scenarios. Therefore, this section compares the DA-based and on-demand in subsections 5.1 and 5.2, respectively. We use real spatiotemporal datasets[42] in the experiment. This dataset is described in detail in the Appendix J.

The experimental parameters are set in Table 2.

TABLE 2: Experimental parameter table

Number of participants set $\mathbb{u}$	$[5, 500]$
Number of tasks set ta	$[100, 1200]$
Independent Measurements per Task ta_k	$[5, 25]$
Task value v_m	$(5, 20]$
Reward budget Bu_i	$[500, 2500]$
Cost coefficient per distance $\vartheta_{i,j}^{ta_m}$	$[0.4, 1.2]$
Data collection cost $c_{i,j}^{data}$	$[1.0, 3.0]$
Participant reinforcement factor s_i	$[0.5, 0.9]$
Participant sensing range	$[50, 100]$
Participant vehicle movement speed	$[0, 75]$

5.1 Comparison of TCPD and DA-based

This section presents a comparative experiment on TCPD and DA-based. The initial experimental environment was the same: the number of tasks was 800, the number of participants was 600, and the area where the participants were concentrated was the hot area.

First, we compared the number of RATs covered by TCPD and DA-based methods. For LDMC, HATs have sufficient participant distribution; therefore, HAT coverage is generally high. RAT coverage is very important because of sparse participant distribution and low task coverage. Fig. 6 shows the number of RATs covered by TCPD and DA-based in a single round within 20 rounds.

As shown in Fig. 6, the number of single-round coverage RATs

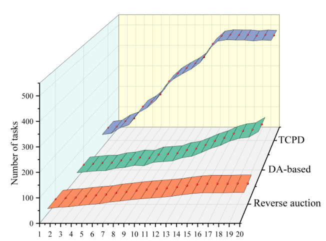

Fig. 6: Comparison of TCPD, DA-based and Reverse auction single-round RAT coverage

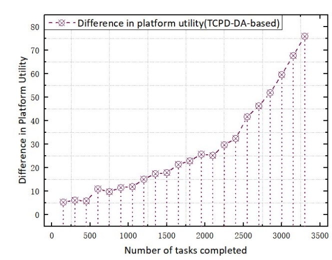

Fig. 7: Total Utility Difference Diagram of TCPD, DA-based and Reverse Auction Platforms

increased in both TCPD and DA-based approaches, but the speed of TCPD increase was faster than that of the DA-based approach, and TCPD remained stable when the number of RAT coverage reached 500. The amount of RAT coverage for the reverse auction mechanism grows slowly, and the overall coverage is low.

Next, we compare the platform utility of TCPD and DA-based methods. The platform utility was calculated by subtracting the total value of the task received by the platform from the reward paid to the participants. In the LDMC real-world scenario, platform cost often has budget constraints. Reducing platform costs and improving the effectiveness of the platform are important aspects of the incentive mechanism. Fig. 7 shows the difference in platform utility between TCPD and DA-based methods when performing the same number of tasks. As shown in Fig. 7, the platform utility difference between TCPD and DA-based platforms is positive; that is, the platform utility of TCPD is always higher than that of DA-based platforms. As the number of tasks completed increases, the difference between TCPD and DA-based platform utility increases gradually; that is, the more rounds the mechanism runs, the larger is the size of the tasks involved and the larger is the platform utility mechanism of TCPD.

The retention rate of the participants in the running process of the mechanism indicated the ability of the mechanism to maintain the participants. In LDMC, remote areas often do not recruit enough participants to complete data-aware tasks because of the small number of participants; therefore, it is important to maintain long-term participation. Fig. 8 shows the change in the retention rate of the participants for the two mechanisms, TCPD and DA-based, in 20 rounds of tasks.

From Fig. 8, we can observe that the participant retention rate

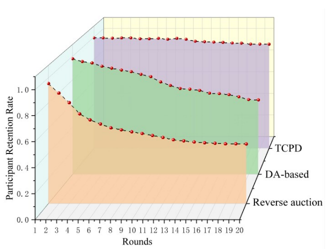

Fig. 8: TCPD, DA-based and Reverse auction participant retention rates

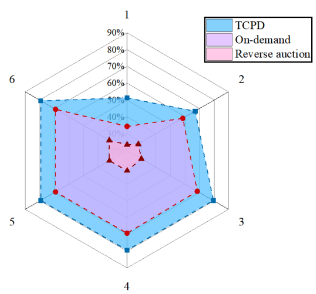

Fig. 9: TCPD, on-demand and reverse auction task coverage comparison

for TCPD remained stable for 1–10 rounds and slowly decreased after ten rounds but remained above 90%. The retention rate of participants in the DA-based mechanism declined rapidly, dropping to 63.8% when the task took 20 rounds. Retention rates for participants in the reverse auction mechanism declined rapidly and eventually remained at 47.4%, an overall low level.

5.2 Comparison of TCPD and on-demand

This section presents a comparative experiment between TCPD and on-demand mechanism. on-demand dynamically adjusts the reward for different tasks according to the weight of demand, routes the participants' shortest paths, and assigns tasks according to their location and distance of movement. on-demand mechanism application background and incentive target are highly consistent with TCPD, and it is also representative of high-level paper mechanisms in the field of MCS; therefore, this study chooses the on-demand mechanism for comparison. Because the on-demand mechanism is complex, computationally complex, inefficient, and accurate in high-load scenarios and performs well in low-load scenarios, the experimental load is reduced for both mechanisms in simulation comparison experiments. The initial conditions of the two mechanism experiments are the same; 10 task locations are distributed on the map, 20 measurements are required for each task, the total number of measurements to be collected is 200, and the number of participants is 50, which is a normal distribution. The area where the participants concentrated was a hot area.

In LDMC, task coverage is an important indicator of how well tasks are completed in remote areas. Fig. 9 shows a comparison of the task coverage.

As shown in Fig. 9, the task coverage under the TCPD mechanism is consistently higher than under the on-demand mechanism. The reverse auction mechanism has the lowest task coverage. After four rounds of testing, the TCPD and on-demand task coverage rates remain stable, with TCPD stabilizing at around 80% and on-demand task coverage stabilizing at around 60%. This is because TCPD performs path cultivation in the early rounds, which increases the participants' expected utility $Uex_{i,j}^{R}$ and the degree of path-dependence $ReT\left(Uex_{i,j}^{R}\right)$ (Discussion of $ReT\left(Uex_{i,j}^{R}\right)$ is shown in Appendix K) for RAT to incentivize the participants to choose RAT, whereas the on-demand mechanism is the optimal path decision, and the participants prioritize HAT, so there is less growth in the task coverage. In later rounds, in TCPD, participants preferred RAT due to path dependence, and according to Formulas (12) and (13), participants moved to remote areas to increase competitiveness, reduce costs, and complete more RATs, and the platform adjusts the true probability $\widetilde{\alpha}_{i,j}^{r}$(Discussion of $\widetilde{\alpha}_{i,j}^{r}$ is shown in Appendix L) of the PM stage to recover costs, whereas the on-demand mechanism used on-demand dynamic allocation of payoffs and increased payoffs for RATs to increase task coverage, which increased the platform cost. Finally, the task coverage of both mechanisms stabilizes due to budget constraints. However, since TCPD adopts cost recovery and incentivizes participants to move to remote areas to reduce costs, while the on-demand mechanism only increases the remuneration of RATs, TCPD is able to achieve higher task coverage under the same budget constraint.

As shown in Fig. 10, in contrast to the on-demand mechanism,

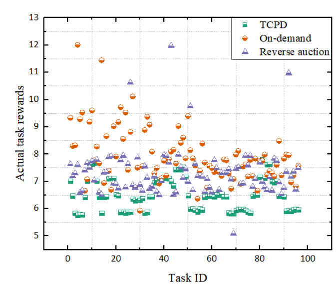

Fig. 10: TCPD, on-demand and Reverse auction task reward distribution comparison

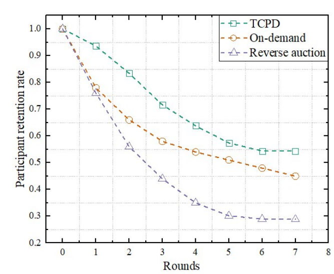

Fig. 11: Comparison of retention rates of TCPD, on-demand and Reverse auction participants

TCPD pays less. The reward distribution for the reverse auction mechanism is between on-demand and TCPD. Compared with on-demand, TCPD fosters probability through cognitive bias, which increases participants' expected utility but decreases their actual utility. It also reduces participants' costs by distributing them to remote areas, which further reduces quotations and results in lower reward. on-demand dynamic reward mechanism incentives participants to participate in RAT by increasing RAT reward, which is costly. The reverse auction mechanism uses a reverse auction to motivate participants' bids, which reduces platform costs but does not have additional incentives for participants to receive RAT; therefore, most of them are HAT rewards.

The participants' retention rate reflects the incentive effect of the incentive mechanism in the time dimension. Because long-term participation in tasks increases the cost of participation, the retention rate of participants will decline with an increase in task rounds. It is critical to encourage participants to participate in tasks for long periods of time. Fig. 11 shows a comparison of the participant retention rates of TCPD and the on-demand mechanism in seven rounds of tasks.

It can be observed from Fig. 11 that with the increase in task rounds, the retention rates of participants in both TCPD and on-demand decreased, but the retention rates of participants in TCPD decreased more slowly. The retention rate of participants in the reverse auction mechanism dropped the fastest and finally remained at a low level of 28.9%. This is because the TCPD mechanism not only cultivates and maintains path-dependence on participants but also sets a dynamic exit tax (Discussion of exit tax base value $Pu_{i,j}^{PM}$ is shown in Appendix M) according to Theorems 3 and 4, which incentivizes participants to continue to participate in the task and improves the user retention rate, whereas the on-demand mechanism only increases the payoffs to incentivize participants to participate without taking into account the increase in participant's cost under multiple rounds, and exiting the task does not affect the participant's utility. Therefore, participants will choose to quit when the cost increases, maintaining the effect of crossover. Therefore, the on-demand mechanism will always have a lower user retention rate than the TCPD mechanism.

The thermal diagram of participant distribution reflects the incentive effect of the platform on participant movement. Fig. 12 shows the initial distribution of participants and the distribution of TCPD and on-demand participants in the fifth task round. Simultaneously, the incentive effect of a reverse auction is added as a reference. To draw the distribution map, 15*15 areas were selected to count the number of participants in each area.

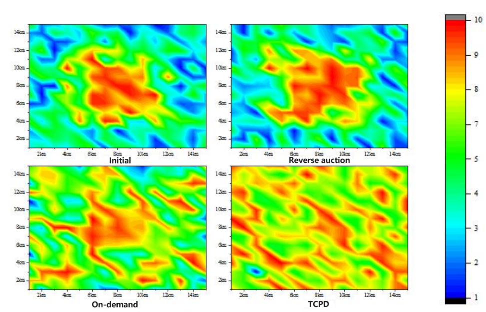

Fig. 12: Distribution of TCPD, on-demand and reverse auction participants

It can be observed from Fig. 12 that in the initial state, the participant mechanism is distributed in hot areas, and the participant density in remote areas is low. The distribution of participants under the incentive of TCPD is relatively balanced, and the coverage of the map is large. Compared with the initial state, the distribution of participants in the on-demand mechanism has expanded to a certain extent, but it is still centered with limited coverage. The reverse auction mechanism has little change, and the participants are still concentrated.

6 CONCLUSION

In this paper, we focus on the difficulty of completing long-term tasks in remote areas. Inspired by the path-dependence phenomenon and based on the real-world environment where uncertain information exists, we propose the TCPD in combination with cognitive bias and the reference effect in behavioral economics, which is used to improve the coverage and longterm data collection in LDMC. In the process of mechanism establishment, this study considers two phases of path cultivation and maintenance. The existence of uncertain information is used to cultivate participants to overestimate the probability of winning the award, so that participants' expected utility for RAT is higher than that of HAT, to incentivize participants to choose RAT. Using reference points to set the exit tax prevents participants from exiting the task prematurely and incentivizes participants to continue participating in the task. The experimental results show that, in the same experimental environment, compared with DA-based and on-demand, TCPD has 23.8% and 10.17% higher task coverage rate and 28.7% and 9.42% higher participant retention rate, respectively.

In future work, we will consider the influence of additional factors on the results and further optimize the parameter combination to achieve better incentive effects. We can also combine the relevant theories of behavioral economics to incentivize participants to submit high-quality data, such as data accuracy, or consider introducing privacy-preserving mechanisms to protect participants' private information.

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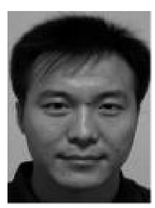

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