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Do Dynamic Signals Affect High-Quality Solvers' Participation Behavior? Evidence from the Crowdsourcing Platform

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Abstract: The emergence of the crowdsourcing platform enables seekers to obtain higher-quality services at lower costs. High-quality services are often provided by high-quality solvers, which is the key to the sustainable development of crowdsourcing platforms. Therefore, how to attract more high-quality solvers to participate needs to be focused on. Most previous studies that used stock data to measure crowdsourcing performance failed to describe the contest process of high-quality solvers' behavior. Different from the previous study, this paper explores the information signals that influence the participation of high-quality solvers in the dynamic process of crowdsourcing contests. Based on the creative projects of the Winvk platform, dynamic models affecting the participation of high-quality solvers are constructed from the perspective of reducing information asymmetry, and the effects of quality signals and intention signals are explored in depth. The results show that for logo design projects, clear information display and monetary mechanisms have a significant impact on alleviating information asymmetry and attracting the participation of high-quality solvers. Interestingly, the effect of market competition on high-quality solvers shows a U-shaped change. The research results provide a reference for enterprises to reduce information asymmetry, obtain high-quality solutions, and enrich the theoretical application in the field of crowdsourcing.

Keywords: crowdsourcing platform; high-quality solvers; signaling theory; quality signals; intention signals

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1. Introduction

To maintain a favorable competitive position, companies need rapid and high-quality innovation [1]. With the development of the Internet, the trend of enterprise innovation is to expand from reliance on internal employees to reliance on external groups [2–4], seeking solutions or product innovations through crowd-based wisdom and expertise. It turns out that a great deal of expertise and knowledge is distributed outside the enterprise. In some cases, crowd intelligence can lead to more effective solutions than enterprise professionals [5]. Large companies can organize by themselves to release projects to attract crowdsourcing solvers. However, this form of crowdsourcing requires high costs and is not suitable for small and medium-sized enterprises. The emergence of crowdsourcing platforms offers a more cost-effective way to bring together enterprises or individuals with needs (seekers) and participants with seeking opportunities (solvers) [6–10]. It can provide a more fluid channel through which enterprises can access large amounts of labor while effectively reducing operational costs. As a typical category of the crowdsourcing platform, creative competitions have clear professional skill requirements, lower project complexity, and a relatively short project period, mainly including logo design, packaging design, etc. [11–14]. Enterprises release their projects on the platform through project descriptions, express their needs and preferences, and reward the best ideas [15].

The keys of previous studies that affect the effectiveness of crowdsourcing performance are quantity and quality. According to the extreme value theorem, a sufficient number of solvers tends to imply having greater high-quality solvers. Therefore, attracting more solvers in a limited amount of time has been the focus of previous studies in the literature. However, Chen et al. [16] conclude that although the number of solvers has a positive effect on participant quality, the distribution of solvers' quality changes over time, and more solvers do not necessarily represent higher performance. Since enterprises ultimately want to obtain the most satisfactory solution, sub-optimal solutions do not contribute to the outcome and can be simply ignored [17]. Therefore, enterprises should directly understand the participation needs of high-quality solvers and make strategic adjustments on how to attract more high-quality solvers [18].

Information asymmetry is an important obstacle to obtaining a satisfactory solution. In creative contests, the seeker does not have a clear goal, and the preference has a certain degree of subjectivity, so there is no unified evaluation standard [19]. For the solver, there is no exact solution. As a result, there is an information asymmetry between the seeker and solver [20]. To reduce information asymmetry and unnecessary inputs, the seeker needs to convey accurate and effective information so that the solver can reduce cognitive bias. Signaling theory is mainly about reducing information asymmetry between two parties [21]. Currently, there are two important types of signals: quality signals and intention signals [22], that can help to make better decisions. Previous studies have mainly used design mechanisms such as price or trust to reduce information asymmetry, which are relatively homogeneous, and the role of different signal types and signal combinations has been ignored. The creative projects are usually broad rather than detailed, and the seeker usually has subjective tastes that cannot be captured by the solver [23]. Therefore, increasing the diversity of signals and disclosing highly accurate information can promote better understanding and reduce cognitive effort when processing relevant information [24]. Therefore, we explore the following question:

RQ1: What dynamic signals influence high-quality solver participation?
RQ2: How do these dynamic signals affect high-quality solver participation?

In order to solve the above problem, this paper divides crowdsourcing into stages of the project process and project completion and focuses on the stage of the project process. Based on the signal theory, we construct the corresponding multiple regression models to analyze the quality signals and intention signals that affect the high-quality solvers. In the project process stage, taking the logo design of the Winvk platform (www.winvk.com) as an example, we crawled the ongoing projects at a fixed time every day. The influence of multiple quality signals, such as information display and multiple intention signals, such as competitive factors, is researched. Our results show that the projects with an upper rank do not necessarily attract more high-quality solvers, so the seeker may not need to consider purchasing value-added services such as project topping in a short period. Second, more views and submissions prevent further participation by high-quality solvers. The research illustrates that market competition shows a U-shaped effect on high-quality solvers as the rating of participants continues to increase. Seekers should focus directly on how to effectively communicate with high-quality solvers to reduce information asymmetry and avoid more suboptimal solutions. Finally, prize mechanisms have a significant role in reducing information asymmetry, and projects with higher relative prizes can attract more high-quality solvers. The results provide suggestions for the seeker to obtain satisfactory solutions quickly and effectively, enrich the research in the field of crowdsourcing contests, and expand the application boundaries of signaling theory.

The paper is structured as follows: Section 2 is the theoretical background on participation behaviors of high-quality solvers and signaling theory. Based on the research background, Section 3 expounds on the dynamic models and hypotheses. Section 4 carries out the concrete empirical analysis. Section 5 discusses the research conclusions and summarizes the theoretical and management significance, and the paper is concluded in Section 6.

2. Literature Review

2.1. The Participation Behavior of High-Quality Solvers

For small and medium-sized enterprises, meeting innovative and differentiated needs is limited by capital and personnel. The emergence of crowdsourcing platforms provides an efficient and convenient channel for enterprises to obtain high-quality solutions, and enterprises can obtain a large amount of labor with time and cost benefits.

Since crowdsourcing contests usually select the best one from multiple solutions, the quantity and quality of top solvers in the contest is a major concern for the seeker [15,25,26]. According to the extreme value theorem, a larger number of solvers represents a larger number of high-quality solvers and, thus, more capable of delivering higher-quality solutions. Therefore, Terwiesch and Xu [20] measure the quality of solvers by the number of solvers. They argue that although an increase in the number of solvers may reduce the effort level of the solvers, the seeker can benefit from a larger group of solvers to an extent that even exceeds the impact due to the lack of individual effort input. Among them, the prize is one of the important factors affecting the participation of the solvers. Previous research has explored the effect of prizes on the number of participants through a field experiment and showed that higher prizes induced more submissions, and manual scoring of the submissions revealed that more submissions led to higher quality [27]. Similarly, Zheng et al. [28] demonstrates that crowdsourcing contests with higher prizes can attract more solvers, including those with the most expertise.

Based on previous research, scholars have studied the relationship between the number of solvers and crowdsourcing performance in greater depth. They suggest that the number of solutions may have a differential impact on quality. Therefore, based on the theoretical model of Terwiesch and Xu [20], Zheng et al. [28] further explore the impact of the quantity and diversity of solutions on solution quality using actual data. The study shows that the quantity and diversity of solutions have a positive impact on quality, but the role of diversity is more significant. In addition, scholars have argued that solvers' previous experience or achievements are a reflection of the quality and can be used as a proxy for crowdsourcing performance. Reputation scores can reflect past solvers' contributions to the platform in terms of quantity and quality. Therefore, Xu et al. [29] explore the impact of the reputation system on the participation of high-quality solvers. Research shows that reputation incentive mechanisms can improve the competitiveness of participants and promote the participation of high-quality solvers. Chen et al. [24] use the number of prizes accumulated from previous contest successes as a proxy for top solvers' quality and focus on exploring the impact of prizes, and period on high-quality solvers. The study argues that the distribution of solvers is not constant over time and, therefore, the number of solvers does not directly represent contest performance. For the above reasons, some studies have begun to use the degree of effort of the participants to represent the quality of participation. Usually, the harder the effort, the more time and energy it takes. Therefore, the probability of providing high-quality solutions is higher [23].

Previous research has paid more attention to the results of crowdsourcing, but the process of crowdsourcing contests can more accurately reflect the change trajectory of the project [30]. Scholars believe that static stock data cannot effectively reflect the changes in project design parameters over time. Therefore, the dynamics of the crowdsourcing contest process have received more attention [31]. Posts with timestamps show the knowledge-sharing trajectory of participants on the crowdsourcing work platform, making the knowledge-sharing trajectory a channel for platform participants to understand and influence each other. Majchrzak and Malhotra [32] first explore the impact of knowledge-sharing trajectories on innovation outcomes. They construct an idea framework of "idea-hypothesis-paradox" to explore the process of an idea from its origin to its eventual achievement of the intended purpose. However, the focus of crowdsourcing contests is to guide more solvers to participate and obtain more high-quality solutions. Therefore, Jiang et al. [31] simulate multiple stages of the crowdsourcing competition by building a dynamic structural model, and explore the impact of feedback on the solver's entry into the

competition, exploration and development of new solutions. Similarly, Sanyal and Ye [30] also posit that feedback is a tool to dynamically improve the efficiency of public competitions. They explore the evolution of submissions based on feedback and dynamically guide participants to reach the final ideal state, rather than just focusing on the results. Since the projects and participants on the crowdsourcing platform do not exist independently, the factors affecting proposal submission are more complex and changeable. Therefore, we need to pay more attention to the changes in project factors that affect the participation of the solver.

A review and comparison of previous studies show that high-quality solutions tend to be provided by more experienced and higher-ranked solvers, yet few studies directly address high-quality solvers. Second, most previous studies use stock data; that is, after the completion of the project, the research collects one-time data to explore the influencing factors. However, the crowdsourcing contest process is continuous and dynamic, and influencing factors change with changes in the environment, which in turn affects the response of high-quality solvers. Existing data cannot reflect the changes in influencing factors during the project process. Capturing the daily changes in the project and obtaining daily flow data will help explore the role of influencing factors on the participation behavior of high-quality solvers during the project process. Therefore, we measure the quality of the solvers by the rating of the solvers and explore the influencing factors of high-quality solvers on the dynamic process. We summarize the relevant studies in Table 1 and compare them with our study.

Table 1. Review of crowdsourcing performance studies.

Authors	Focus	Main Factors	Data Type
Terwiesch and Xu [20]	Effort level	Number of competitors; Prize structure	Stock
Liu et al. [27]	Number of participants; Solution quality	Prize	Stock
Zheng et al. [28]	Solution quality	Number of solutions; Diversity of solutions	Stock
Boudreau et al. [33]	Crowdsourcing performance	Number of competitors	Stock
Chen et al. [16]	Crowdsourcing performance	Prize; Period	Stock
Jiang and Wang [23]	Participant quality	Prize; Period	Stock
Gao et al. [21]	Crowdsourcing performance	Quality Signal; Trust	Stock
Jiang et al. [31]	Crowdsourcing performance	Feedback	Flow
Sanyal and Ye [30]	Solutions convergence and diversity	Feedback	Flow
Our paper	High-quality solver	Quality signal; Intention signal	Flow

2.2. Signal Theory

In the crowdsourcing platform, the seeker attracts many solvers to obtain solutions by releasing projects. Since the seeker does not have an exact target, evaluation criteria are subjective, and the solver cannot fully capture the needs of the seeker and conduct an accurate analysis, thus creating an obvious information asymmetry between the two parties. Reducing the asymmetry between the two parties helps the solver to make better judgments about the requirements and thus decide whether to participate in the project. The core of signaling theory is about reducing information asymmetry [21], so it can reasonably explain the behavior of seekers and solvers on the crowdsourcing platform.

The signaling theory was originally used to describe the information asymmetry between the sending and receiving in various economic and social contexts. It explains that the party with the information advantage transmits information to the party with the information disadvantage through a variety of signals. Since both parties do not always have access to the same information [34,35] and interpret the information in the same way, high-quality and diverse signals are needed to communicate in order to obtain the desired

outcome [36]. The signaling theory to reduce information asymmetry mainly includes quality signals and intention signals. Quality signals mainly refer to the information communication between two parties, and intention signals refer to the intention and behavior of participation. In crowdsourcing platforms, especially in the creative project, which usually involves extensive and non-detailed project descriptions, the seekers have private and subjective tastes for potential solutions that cannot be fully captured [20,37]. In order to reduce information asymmetry and obtain optimal solutions, the seeker needs to describe the requirements in as much detail as possible without revealing confidentiality and reduce the cognitive bias of the solver. The goal of the seeker is to use signaling theory to get more solvers focused on their project and willing to participate in the project, so that both parties can reach an exchange or cooperation.

In order to reduce the problems caused by information asymmetry, indicators such as price, guarantee, or reputation can be used to identify the quality of their products or services [38]. Based on uncertainty reduction theory, Yang et al. [39] explores the impact of the platform's assurance mechanism on the behavior of the solvers. The result shows that the assurance mechanism can provide different kinds of quality information to meet the information needs of solvers and effectively reduce information asymmetry, thus building trust between seekers and the solvers. Some studies believe that crowdsourcing online collaborative communities can replace traditional signaling mechanisms. Because crowdsourcing platform information is more transparent, stakeholders can effectively exchange information and reduce search costs [40]. Gao et al. [21] use information signaling theory for the first time in the crowdsourcing field to construct a mechanism for online reputation and salary comparison to reduce information asymmetry. The results show that reputation and salary positively affect the participation behavior of the solvers, which has important implications for how to design project mechanisms to motivate solvers' participation. From the perspective of the seeker, Pollok et al. [41] argue that a clear statement can reduce uncertainty and increase willingness to participate among potential solvers. Therefore, based on uncertainty reduction theory, they explore the relationship between information disclosure and the attention of solvers. Adopting a complementary perspective, Piazza and Perrone [42] posit that the solver's personal profile and blog can indicate their abilities and skills, and both serve as important skill signals to attract the attention of the seeker. In addition, examples [43] and feedback [30] reduce the information asymmetry between the project parties by providing more intuitive reference materials and raising further requirements for the current problem, which can reduce the solver's cognitive cost and effort.

Current research has realized the importance of reducing information asymmetry, and signaling theory has received widespread attention as an important theory for mitigating information asymmetry through signals. Connelly et al. [44] review the application of signaling theory in various management literature through the three key components of the signal timeline. However, current research focuses more on quality signals and does not integrate the impact of multiple signals. Second, markets operate in a dynamic environment, and effective information is also constantly changing. However, previous studies are based on static signals, without considering the variation in the signal over time and the difference in its impact. Scholars have considered the dynamic development process of crowdsourcing and explored the impact of feedback on dynamic performance from the perspective of the seeker [30,31]. However, what is revealed about the changes over time in the project itself is also worthy of attention. Therefore, we will analyze the influence of multiple dynamic signals from two aspects (quality signal and intention signal) and explore the signal mechanism design of the crowdsourcing platform based on signaling theory.

3. Research Framework and Hypotheses

The crowdsourcing competition process is generally divided into two stages: project progress and project completion, as shown in Figure 1. Most previous studies have analyzed only the completed project, ignoring the impact of changes in the project process. Although

the latest research has paid attention to the dynamics of crowdsourcing contests, their studies are limited to the role of feedback signals in the crowdsourcing process [30,31]. For small and medium-sized projects, short-term factor changes have an important impact on the behavior of participants. Therefore, in order to supplement previous research content, we focus on the impact of signal factors in the project process on high-quality solvers.

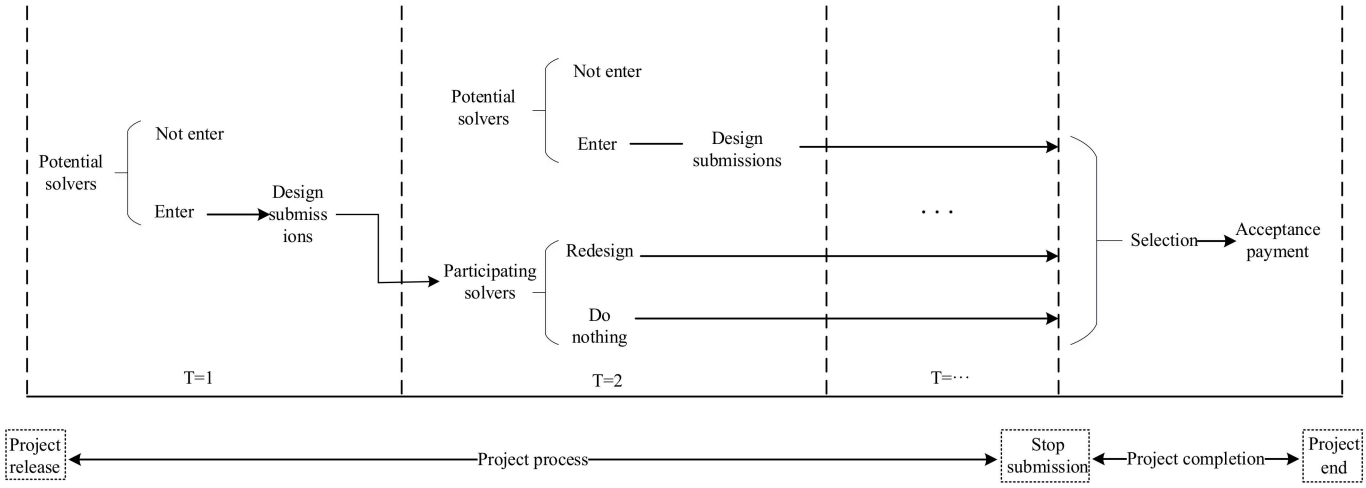

Figure 1. Crowdsourcing contest project process.

The key to the success of a crowdsourcing contest is enough participants and crowdsourcing performance. For logo design projects, most projects will only select an optimal solution and pay prizes to the winners. According to the research of Chen et al. [16], more participants will not necessarily lead to higher crowdsourcing performance. High-quality solvers are more likely to provide high-quality solutions because of their rich experience and successful experience. In addition, when the seekers have a large number of solutions, they are required to spend time and energy evaluating and screening the solutions to find the best solution. If the differences between solutions are significant, the seekers need to make extra efforts to judge and select [42]. At this point, if the seeker has limited time, they may be more inclined to focus on options that require less attention and understanding. Therefore, seekers can consider filtering out low-quality solvers first during the project to reduce cost waste. Based on the above reasons, we choose to research high-quality solvers to explore what signals will affect their participation.

In addition, crowdsourcing connects the seekers and the solvers through an online platform rather than traditional face-to-face communication and exchange. Therefore, information asymmetry is a common problem faced by crowdsourcing contest projects. The seeker designs the project framework [45] and releases the content, including title, details, prizes, duration, etc. The solver uses this information to make judgments and choose whether to participate. Since the seeker has their own personal taste and the solver has their own interpretation of the project requirements, information asymmetry occurs between the two parties. Only by reducing information asymmetry can the seeker obtain the most satisfactory solution [46]. Signaling theory is mainly used to describe and explain the phenomenon of information asymmetry between stakeholders, and how to alleviate information asymmetry through signals. Since crowdsourcing projects are dynamic, the signals change accordingly. Therefore, dynamic signals can more accurately reveal project and environmental information and help the solver make decisions.

Based on previous research and signaling theory, the dynamic influencing factor model is constructed as shown in Figure 2. The influence of quality signals and intention signals on the participation behavior of high-quality solvers is explored. Quality signals include the location (page number, sorting) and deadline (remaining time), and intention signals include the view, submission, relative prize and market competition. Titles and details will

not change once they are released, but they have an impact on the solver's understanding and participation in the project, so they are added to the model as control variables.

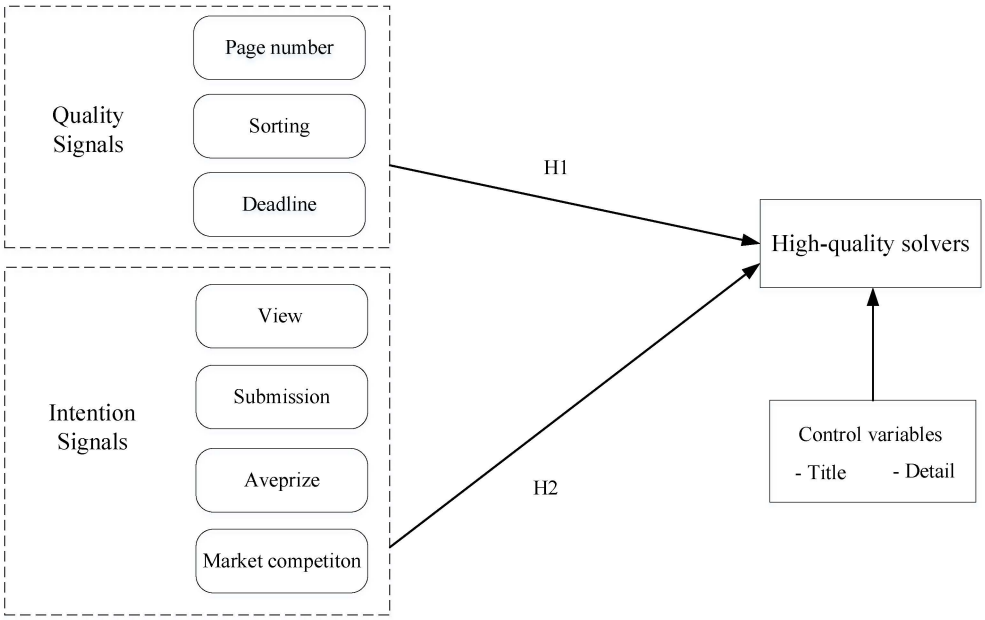

Figure 2. Dynamic influencing factor model.

3.1. The Impact of Quality Signals on the Participation Behavior of High-Quality Solvers

Quality signals focus on the information asymmetry that occurs when one party does not fully understand the characteristics of the other [44]. To reduce the impact of information asymmetry between parties, the party with more information needs to disclose certain content to the party with less information. Quality signals provide the solver with the basic situation of the project and help the solver understand the requirements. The location of a project reveals when it was released and how urgent it is. The main reasons the project is located higher are as follows: (1) the project is the latest release because the platform's arrangement rules are based on time; (2) the project is urgent or important, and the seeker increases its exposure by purchasing additional services such as project pinning. They hope to attract more solvers to participate in a shorter period, reduce time and labor costs, and obtain satisfactory solutions. The remaining time represents the time until the end and can reflect the urgency of the project. Projects with a looser schedule may generate more brainstorming, enhance the motivation of high-quality seekers to participate, and obtain more innovative and high-quality solutions. From the signaling theory perspective, quality signals should be concise, complete, and easy to understand [47] so that high-quality solvers can understand project requirements, generate ideas, and propose solutions [48].

The sequential effect describes the impact of the order of presentation on choice, which includes the primacy effect and the recency effect. The primacy effect refers to the fact that the first impression of the first thing that appears is the more impressive and has a dampening effect on things that appear later. The recency effect refers to the fact that the later the appearance, the clearer the impression left, which overwrites the impression of what appeared earlier. Longer project periods make this phenomenon more pronounced.

Due to behavioral habits, people usually browse from the beginning, and there is a diminishing marginal effect on cognition when there are too many same types of projects. Some studies believe that participants are more likely to pay attention to the latest content, and their attention to things will decay over time [49]. Projects on the relatively front page and higher sorting can attract more attention, so the crowdsourcing platform provides services such as project topping to meet the needs of the seeker. According to signaling theory, high-quality signals have clear and distinctive characteristics, which can reduce the unnecessary search and judgment of the solver and provide a more direct reference.

Projects in higher sorting can reduce the cognitive effort of the solver, especially the top location projects, which can reveal the current status of the project, that is, the project has not received a satisfactory solution or the project is urgent. It is a relatively more favorable signal for the high-quality solver, because the high-quality solver is often able to provide a higher-quality solution in a shorter period. We hypothesize the following:

Hypothesis 1a. *Projects with relative front pages can attract more high-quality solvers to participate.*

Hypothesis 1b. *Projects with higher sorting will attract more high-quality solvers to participate.*

The auction literature has found that the project period has a positive effect on the number of participants. The longer the period, the greater the number of people observing and participating in a given auction [50–52]. Similarly, in crowdsourcing projects, the longer the period, the more time the solvers will have to solve the challenges presented by the seeker [53]. However, during the project process, the solver pays more attention to the remaining time of the project. The remaining time is the time left until the end of the project. The number of days until the deadline displayed directly on the platform allows the solvers to clearly understand the progress of the project and weigh in on whether they can participate and deliver a quality solution [54]. The longer the time left, the more time can be provided for the solver to think and conceive, especially for high-quality solvers who pursue excellence and constantly revise their ideas. According to signaling theory, a longer remaining time means the solver has more time for ideation and design, which can provide a higher quality solution. We hypothesize the following:

Hypothesis 1c. *The longer the remaining time, the more high-quality solvers can attract to participate.*

3.2. The Impact of Intention Signals on the Participation Behavior of High-Quality Solvers

Intention signals focus on the relationship of one party to the behavior or intent of the other party [44]. For crowdsourcing contests, the purpose of the solver is to obtain the prize, and the intention signal affects the solver's perception of the probability of winning, thereby affecting the decision-making. Intention signals come from inside the task and outside the environment. View and submission come from internal signals, which can reflect the attractiveness of the solvers and also indicate the competition within the project. If competition is perceived to be strong, the solver will have negative emotions, leading to the choice to withdraw from the project competition. Relative prizes and market competition come from external signals. A higher relative prize means that the solver can obtain richer rewards for participating in the project within the same period, which is an important external incentive. Market competition represents the number of the same projects in the same period, which reflects the demand in the entire market. More demand means more choices for the solver. The opportunity cost of the abandoned project can be obtained through another project to make up for it. From a signaling theory perspective, solvers can utilize intention signals when processing and interpreting their choices and weighing the probability of benefiting from completing the work [55].

The competitive nature of crowdsourcing contests can affect the motivation of the solvers to participate and the effort put into the project [33]. Competition includes competition within the project and outside the market. Competition within a project usually refers to the attention of different people to the same project. On the crowdsourcing platform, the two signals of daily view and submission reflect the attention and solutions received by the project in real time. More views indicate that more potential solvers may be attracted. More submissions represent more actual solvers who need to put in real-time and experience costs. Chen et al. [16] conclude that since projects in the market do not exist independently and the quality distribution of competitors is not invariant, more participants imply higher competition. In addition, the process of waiting for results has paid time and opportunity costs. If the time course is delayed, the advantage of high-quality receivers is weakened,

and it is clear that high-quality solvers are less likely to enter projects [56]. We hypothesize the following:

Hypothesis 2a. *More views will reduce the participation of high-quality solvers.*

Hypothesis 2b. *More submissions will reduce the participation of high-quality solvers.*

Motivation theory demonstrates that one of the most significant motivating factors is getting paid. Since it takes effort and time for solvers to submit solutions, solvers will only be willing to put in real action if they receive prizes that cover the costs, especially high-quality solvers with expertise. Liu et al. [27] demonstrate through a field experiment that the higher the prize, the higher the average quality of the acquired solutions. In the crowdsourcing platform, the solvers can learn about all the ongoing projects and the prizes corresponding to the projects. Based on the market price, the solver can compare different projects and measure the relationship between cost and performance, and the projects with higher relative prizes have better compensation for the cost. Since the market competition can be judged by the number of projects that exist at the same time, the probability of receiving the final prize can be evaluated. Consider that the number of active solvers in a certain period of time is relatively fixed and will not increase suddenly. Therefore, the greater the competition in the market, the fewer high-quality solvers a single project can attract, and the probability of obtaining the final prize increases. The intention signal focuses on the behavioral intent of the solver, and receiving the ultimate prize is an important driver. We hypothesize the following:

Hypothesis 2c. *A higher the relative prize increases the participation of high-quality solvers.*

Hypothesis 2d. *Greater market competition reduces the participation of high-quality solvers.*

4. Methodology

4.1. Data

For the proposed research hypothesis, we collected data from the Winvk platform, one of the largest crowdsourcing platforms in China. The Winvk platform was created in 2006, and it currently has over 10.44 million members and has released over 420,000 projects with a total prize of over RMB 2.1 billion. By paying prizes in advance, anyone can post projects on the platform by offering prizes or bidding methods, and the payment of prizes in advance reduces the problem of moral hazard arising from information asymmetry. In this paper, the main reasons for choosing the project of logo design are as follows: first, the design category projects on the Winvk platform accounted for about 78.4% of the total competition projects [28]. Among them, the logo design category projects can attract more solvers because of the clear professional skill requirement, and there is high variability between solvers of different qualities. Second, the logo design project period within 10 days accounted for more than 80%. The project period is shorter, and the dynamic changes are significant, which better reflects the impact of dynamic data. Third, logo design is a type of creative project where the differences in individual tastes and expressions of the seekers make the information asymmetry more prominent [20]. Although the Winvk platform focuses only on the Chinese market, the market itself is huge and, therefore, can provide rich data for this paper's research, making the paper's findings representative.

The platform of Winvk is open for completed projects and ongoing projects. Since the previous research on static models is relatively complete, this paper focuses on the research on dynamic models for the analysis of an ongoing project process. The data for the dynamic model include all ongoing projects from 1 March 2021 to 31 May 2021, and the data for the projects were crawled at regular intervals each day to obtain dynamic and continuous data. After basic cleaning, a total of 5661 data were obtained for the follow-up research. Table 2 shows an example obtained by structurally transforming the crawled original content.

Table 2. Examples of structured transformations.

Variable	LOGO Design	Institute Logo Design	...	Font LOGO Design
Detail	106	5		35
Supplementary	1	0		5
Period	24	4		2
View	1475	267		325
Submission	92	22	...	29
Prize	770	300		100
Distribution	One winner	One winner		Multiple winners
Crown quantity	34	12		21
Non-crown quantity	58	10		14

4.2. Measures

According to the research content of this paper, the quality signal and intention signal that affects the high-quality solvers are explored, and the dynamic variable model is constructed for the stage of project process. The solvers are classified according to their rating. The ratings from low to high are as follows: no grade, star, diamond, crown, and golden crown. Crown-level and above solvers are defined as high-quality solvers. Therefore, the dependent variable is the participation behavior of high-quality solvers, that is, the proportion of the daily submissions of solvers at crown level and above to the total daily submissions of solvers at all levels. The independent variables mainly include quality signals (page number, sorting, deadline) and intention signals (view, submission, relative prize and market competition), and the control variables are the title and detail of projects. The main variables and explanations are shown in Table 3.

Table 3. Dynamic model variables and definitions.

Variable Type	Variable	Definition
Dependent variable	High-quality	The proportion of daily submissions of solvers at crown level and above to the total daily submissions of solvers at all levels
Independent variables	Page	Page number displayed on the platform
	Sorting	Order of projects on each page
	Deadline	Time left until end
	View	Views of daily projects
	Submission	Submissions of daily projects
	Prize	The difference between the project prize and the average daily prize for all projects in progress
	Competition	The total number of projects in progress per day
Control variables	Title	Number of characters in the title
	Detail	Number of characters for the specific content

4.3. Empirical Specification

The research models for dynamic variables mainly include time series analysis, panel data analysis, and linear regression [53,57]. Considering that the projects researched in this paper do not have the same period, they belong to multidimensional dynamic data and have different dimensional lengths. Based on the form and practical implications of the data in this paper, the research model is finally constructed to explore the effects of dynamic quality and intention signals on the participation behavior of high-quality solvers.

$$High-quality_{i,t} = \beta_0 + \beta_1 \ln(Page_{i,t-1}) + \beta_2 \ln(Sorting_{i,t-1}) + \beta_3 \ln(Deadline_{i,t-1}) + \beta_4 \ln(View_{i,t-1}) + \beta_5 \ln(Submission_{i,t-1}) + \beta_6 \ln(Prize_{i,t-1}) + \beta_7 \ln(Competiton_{i,t-1}) + \gamma X_{i,t} + \varepsilon_{i,t}$$

The descriptive statistics and correlation analysis of dynamic variables are shown in Tables 4 and 5, and it can be found that there are no special correlations that need attention.

In addition, the model is diagnosed for multicollinearity in this paper, and the VIF of all variables is <5, so there is no problem with multicollinearity.

Table 4. Descriptive statistics of dynamic model variables.

Variable	Min	Max	Mean	SD
High-quality	0.00	1.00	0.60	0.15
Page	1.00	9.00	2.12	1.51
Sorting	1.00	43.00	15.41	9.54
Deadline	0.00	40.00	5.76	6.99
View	0.00	3030.00	367.22	372.05
Submission	1.00	250.00	37.37	27.03
Prize	0.23	9.23	1.02	1.07
Competition	48.00	84.00	70.95	7.72
Title	3.00	33.00	9.63	4.85
Detail	2.00	1980.00	116.00	181.48

Table 5. Correlation analysis of dynamic model variables.

Variable	1	2	3	4	5	6	7	8	9	10
1 High-quality	1									
2 ln (Page)	−0.008	1								
3 ln (Sorting)	0.043 **	−0.098 **	1							
4 ln (Deadline)	0.119 **	−0.170 **	−0.079 **	1						
5 ln (View)	−0.296 **	0.354 **	−0.072 **	−0.068 **	1					
6 ln (Submission)	−0.184 **	0.105 **	−0.127 **	0.099 **	0.678 **	1				
7 ln (Prize)	0.056 **	0.082 **	−0.143 **	0.183 **	0.536 **	0.633 **	1			
8 ln (Competition)	0.015	0.042 **	0.033 *	−0.045 **	−0.083 **	−0.064 **	−0.018	1		
9 ln (Title)	−0.013	0.017	0.001	0.035 **	−0.028 *	0.110 **	0.106 **	0.005	1	
10 ln (Detail)	0.137 **	0.154 **	−0.064 **	0.219 **	0.214 **	0.174 **	0.354 **	−0.054 **	0.111 **	1

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Since the signal is in constant change during the project process, there is a certain bias to study only static data; especially for logo design projects with a short period, the dynamic study may be more meaningful, so we constructed a multiple linear regression model and conducted an empirical analysis. The results are shown in Table 6. Page number ($\beta_1 = 0.036$, $p < 0.001$), sorting ($\beta_2 = 0.012$, $p < 0.001$), deadline ($\beta_3 = 0.006$, $p < 0.01$), view ($\beta_4 = -0.087$, $p < 0.001$), submission ($\beta_5 = -0.018$, $p < 0.001$), relative prize ($\beta_6 = 0.128$, $p < 0.001$), and market competition ($\beta_7 = -0.033$, $p < 0.05$) have significant effects on the participation behavior of high-quality solvers.

Table 6. Results of multiple regression analysis.

	Model 1	Model 2
Contant	0.561 *** (0.011)	1.147 *** (0.072)
ln ($Page_{it}$)		0.036 *** (0.003)
ln ($Sorting_{it}$)		0.012 *** (0.002)
ln ($Deadline_{it}$)		0.006 ** (0.002)
ln ($View_{it}$)		−0.087 *** (0.003)
ln ($Submission_{i,t}$)		−0.018 *** (0.004)
ln ($Prize_{it}$)		0.128 *** (0.007)
ln ($Competition_{it}$)		−0.033 * (0.016)
ln ($Title_i$)	−0.010 * (0.004)	−0.023 *** (0.004)
ln ($Detail_i$)	0.015 *** (0.001)	0.013 *** (0.001)

Table 6. *Cont.*

	Model 1	Model 2
R^2	0.020	0.200
ΔR^2	0.019	0.199
F	56.359 ***	157.423 ***

Note: Standard errors are reported in parentheses; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

In the quality signal, the sorting of the project has a positive relationship with the high-quality solvers. In the data obtained in this paper, it is found that more than 90% of the projects are concentrated in the first three pages, which does not waste much cognition, especially for the high-quality solver. Since they have relatively higher professional knowledge and skills, they can quickly complete the solution and optimize it. In addition, the solver is not able to participate in the project at the first time when the project is released, as specific research and creation of the solution are required. Although the location of the project is constantly backward, the time for its change is relatively short, so it does not affect the participation of high-quality solvers. H1a and H1b are the opposite of the hypothesis.

The longer the remaining time, the more high-quality solvers can be attracted. In logo design projects, 80% of the project period is less than 10 days, while the average period is less than 7 days. Therefore, extending the duration within a reasonable task period can effectively attract high-quality solvers. Seekers need to set reasonable deadlines for releasing projects, and dynamic research can observe dynamic changes during the project, including whether the project ends early and whether the project is extended. Usually, after viewing and deciding to participate, the solvers need to conceive solutions based on the limited information revealed by the seeker, and high-quality solvers may choose to continuously revise and improve it to submit a higher quality solution. As deadlines become shorter, high-quality solvers weigh the benefits and costs, and may give up submitting solutions if the costs are too high. H1c is supported.

In the intention signal, the number of views and submissions of a project has a negative impact on high-quality solvers. More views of a project represent more potential solvers, including high-quality solvers. Viewing is a general observation of the ongoing project and is a prerequisite for deciding whether to submit a proposal. The number of submissions is the number of solvers who have participated. Both the number of views and submissions indicate the level of competition. In addition, with the increase in project time, more opportunities for low-quality solvers can be given to participating, but the participation cost of high-quality solvers will increase. Therefore, H2a and H2b are supported.

Projects with higher relative prizes can attract more high-quality solvers. Prizes are considered one of the most important external incentives and are the best compensation for the cost of time and effort expended. The higher the prize, the better the compensation for the cost. A higher prize relative to others of the same type and period represents a more attractive and often attracts more high-quality solvers. Higher market competition means more projects in the same period; however, the number of high-quality solvers does not increase in a short period, so competition will form between different projects, and the participation of high-quality solvers will be dispersed. H2c and H2d are supported. The empirical test results are shown in Table 7.

In addition, we find that titles have a negative impact on high-quality solvers; that is, projects with simpler titles can attract more solvers to participate. The solver's first impression of the project comes from the title. It plays a guiding role and is related to whether the solver is willing to have a deeper understanding of the project content. A concise and clear title can enable the solver to understand the needs of the seeker the first time and make a preliminary judgment. Project details have a positive impact on high-quality solvers. Usually, relatively detailed content can more clearly express the needs of the seeker [58], which can effectively reduce information asymmetry and improve efficiency and solution quality.

Table 7. Hypothesis test results.

No.	Research Hypothesis	Results
H1a	Projects with relative front page can attract more high-quality solvers to participate.	Not supported
H1b	Projects with higher sorting will attract more high-quality solvers to participate.	Not supported
H1c	The longer the remaining time, the more high-quality solvers can attract to participate.	Supported
H2a	More views will reduce the participation of high-quality solvers.	Supported
H2b	More submissions will reduce the participation of high-quality solvers.	Supported
H2c	A higher relative prize increases the participation of high-quality solvers.	Supported
H2d	Greater market competition reduces the participation of high-quality solvers.	Supported

4.4. Robustness Tests

The test of robustness is generally for variable operationalization and definition. First, important control variables are added. The supplementary statement is the feedback on the current submissions, which expresses the attitude and further requirements for the currently submitted schemes, so it has an important impact on high-quality solvers. Moreover, considering that the number of wins is not uniform in different projects, there are two distribution methods: "one winner" and "multiple winners". The distribution of prizes of multiple winners increases the probability of receiving a prize. However, cost signaling is a key consideration for high-quality solvers, and the way multiple winners are distributed reduces the effect of compensating costs. Therefore, this paper adds "supplementary" and "distribution method" as new control variables to conduct the experiment. The results are shown in Table 8. All results are consistent with the main model.

Table 8. Regression analysis with added control variables.

	Model 1	Model 2
Contant	0.581 *** (0.011)	1.143 *** (0.072)
ln ($Page_{it}$)		0.037 *** (0.003)
ln ($Sorting_{it}$)		0.012 *** (0.002)
ln ($Deadline_{it}$)		0.006 ** (0.002)
ln ($View_{it}$)		−0.084 *** (0.003)
ln ($Submission_{i,t}$)		−0.021 *** (0.004)
ln ($Prize_{it}$)		0.131 *** (0.007)
ln ($Competition_{it}$)		−0.032 * (0.016)
ln ($Title_i$)	−0.012 ** (0.004)	−0.024 *** (0.004)
ln ($Detail_i$)	0.014 *** (0.001)	0.012 *** (0.001)
ln ($Supplementary_i$)	−0.010 *** (0.001)	−0.004 *** (0.001)
$Distribution_i$	−0.012 (0.015)	−0.038 ** (0.014)
R^2	0.033	0.204
ΔR^2	0.033	0.202
F	48.920 ***	131.537 ***

Note: standard errors are reported in parentheses; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Second, the measure of high-quality solvers is changed. The dependent variable is replaced in this paper; high-quality criteria are further increased. That is, the number of submissions by the top five solvers (Top5) serves as a proxy for high-quality solvers' participation behavior. To further refine the impact, the behavior of the top four (Top4) and top three (Top3) solvers is also explored. The empirical analysis is re-performed, and the results are shown in Table 9. All variables except market competition are consistent with the results of the main experiment, while Top5 has a negative effect, Top4 does not have a significant effect, and Top3 has a positive effect. It can be found that market competition shows a U-shaped effect as the rating of the solver rises; that is, it has a negative effect for medium and high-ranking solvers, and the negative effect gradually becomes weaker as the rating rises until it becomes a positive effect. The findings are consistent with those studied by Boudreau et al. [33]. In summary, the results of this paper are reliable and can provide support for the theory of this research.

Table 9. Regression analysis with varying dependent variables.

	Top3	Top4	Top5
Contant	0.195 *** (0.045)	0.525 *** (0.053)	1.158 *** (0.064)
ln ($Page_{it}$)	0.034 *** (0.002)	0.046 *** (0.002)	0.041 *** (0.003)
ln ($Sorting_{it}$)	0.007 *** (0.001)	0.010 *** (0.002)	0.012 *** (0.002)
ln ($Deadline_{it}$)	0.009 *** (0.001)	0.011 *** (0.001)	0.004 * (0.002)
ln ($View_{it}$)	−0.024 *** (0.002)	−0.036 *** (0.003)	−0.065 *** (0.003)
ln ($Submission_{i,t}$)	−0.038 *** (0.003)	−0.049 *** (0.003)	−0.066 *** (0.004)
ln ($Prize_{it}$)	0.083 *** (0.004)	0.086 *** (0.005)	0.123 *** (0.006)
ln ($Competition_{it}$)	0.034 ** (0.010)	−0.003 (0.012)	−0.061 *** (0.014)
ln ($Title_i$)	−0.003 (0.003)	−0.015 *** (0.003)	−0.028 *** (0.004)
ln ($Detail_i$)	0.014 *** (0.001)	0.014 *** (0.001)	0.010 *** (0.001)
ln ($Supplementary_i$)	−0.004 *** (0.001)	−0.002 ** (0.001)	−0.002 * (0.001)
$Distribution_i$	0.003 (0.009)	−0.021 * (0.010)	−0.034 ** (0.012)
R^2	0.226	0.239	0.278
ΔR^2	0.224	0.238	0.277
F	149.590 ***	161.300 ***	197.980 ***

Note: Standard errors are reported in parentheses; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

5. Discussion and Implications

The development of information technology has changed the nature of participation in creative contests. Through crowdsourcing, enterprises can obtain a large number of solutions at a lowest cost; however, the ultimate goal of enterprises is to obtain the best and most suitable solution. Research shows that high-quality solutions are often submitted by more experienced and professional high-quality solvers, so attracting more high-quality solvers to participate is the focus of attention. Since the crowdsourcing contests are in the process of dynamic change, this paper explores the signal factors affecting the participation behavior of high-quality solvers from the stage of the project process.

The results show that dynamically changing quality and intention signals have a significant impact on the participation behavior of high-quality solvers. The interesting points are as follows: first, the location of the project is positively correlated with the participation behavior of high-quality solvers, mainly because (1) most of the projects obtained in this paper have a short period, and the location of projects are more than 90% concentrated in the first three pages, so the location does not waste much cognitive effort of the solvers. (2) The location of the project changes over time, but high-quality solvers are not the first to submit solutions because they need to analyze and conceive of a solution that can minimize the impact of information asymmetry and improve the winning rate. The lag in the submission time of high-quality solvers has a certain impact on the results.

Second, view and submission have a negative impact on the participation of high-quality solvers. View represents the number of potential solvers, and submission represents actual existing solvers. Both can reflect the competition situation of the project. As time increases, high-quality solvers have higher time costs. Increased competition and costs reduce the participation of high-quality solvers [59].

Third, market competition has different impacts on solvers with different ratings. Studying through completed projects, Boudreau et al. [33] found that the impact of competition is close to zero for competitors with the lowest ability, becomes increasingly negative relative to competitors with medium ability, and then becomes less negative, and eventually becomes positive for competitors with high ability. However, their model is more appropriate for dynamic project research, which is further validated in this paper using in-process projects. The results show that market competition has a U-shaped effect on high-quality solvers. That is, it first shows a significant negative effect, and as the rating increases, the effect of market competition is first insignificant and then positive, which is consistent with the existing findings.

Finally, static signals also have an important impact on the participation of high-quality solvers. A concise title and detailed project requirements can attract more high-

quality solvers to participate. Jiang et al. [60] explore the role of design specifications in crowdsourcing contests, positing that providing more implementation guidelines at the start of the project can motivate participants to put in more effort. Wu et al. [58] further conceptualize the description as a language signal and explore the impact of information language and emotional language signals on the participation behavior of the solvers. Their results demonstrate that language accuracy had a significant positive effect on solver participation. Therefore, the concise and clear title allows the solver to understand the seeker's needs at a glance, and the detailed content description provides effective guidance for specific implementation.

5.1. Theoretical Significance

This paper has important theoretical implications for exploring the participation behavior of solvers in the crowdsourcing field. First, this paper presents research on high-quality solvers, which is a supplement to previous studies in the crowdsourcing field that only focus on solvers' participation behavior. Previous research has concluded that the key to the success of crowdsourcing contests are quantity and quality of solvers [61,62], and studies are usually conducted on how to improve the quantity or quality of solvers. Because crowdsourcing quality is difficult to measure effectively, a variety of different measures have been derived, but few studies have been conducted directly on participants of different qualities. Studies have shown that high-quality solutions tend to be provided by more specialized, higher-ranked solvers. Thus, directly addressing high-quality solvers, we explore the signaling factors that influence the participation behavior of high-quality solvers and provide a more intuitive discussion of how to access high-quality solutions.

Second, this paper constructs a model from the stage of the project process, which enriches the research content and methods in the field of crowdsourcing. Most of the previous studies only focus on the project completion stage and use static variables to build corresponding models. However, with the continuous development of crowdsourcing platforms, scholars have realized that the crowdsourcing process is divided into different stages and should not only focus on the final results. Therefore, Wen and Atakan [63] conduct research on the request initiation stage to understand the impact of crowdsourcing announcements on consumers' perceptions and behaviors. However, the market environment is dynamic, and information signals are not static and will change with time and the environment. Jiang et al. [31] construct a dynamic structural model to clarify feedback's intertwined impact on solvers and potential solvers during the crowdsourcing contest process. Similarly, Sanyal and Ye [30] also classify feedback into process feedback and result feedback, exploring the role of dynamic feedback in improving crowdsourcing performance. Although current research has focused on the important impact of the dynamics of crowdsourcing contests on the participation behavior of solvers, the research treats the project as an independent existence in the platform, and the research content is relatively single. Considering the existence of multiple different projects in the market at the same time and that projects do not exist independently, this paper explores the creative projects of the entire crowdsourcing platform and focuses on the impact of multiple dynamic signals generated during the project process.

Finally, from the perspective of signal theory, the research enriches the relevant literature on signal theory. In the past, the application of signaling theory was more concentrated in communities and social platforms [64]. With the increasing use of crowdsourcing platforms, signaling theory has received widespread attention in the field of crowdsourcing. Since the crowdsourcing platform connects professionals and demanders worldwide through the Internet, there is an obvious information asymmetry between the seeker and the solver. Signaling theory provides a practical and unique perspective on choice problems under conditions of incomplete information [44]. By reducing the information asymmetry between the two parties, solvers can have a more comprehensive and accurate understanding of the seeker's needs, which could effectively improve the quality of the solution. For example, reputation signals [29] and skill signals [42] can indicate participants' abilities; language signals [58] and

information signals [58] can clearly express the needs of the seeker and effectively reduce the uncertainty of both parties in the project. However, the current research on signals is relatively single and cannot show the dynamic changes of signals during the crowdsourcing contest. Based on the above reasons, this paper investigates the reduction in information asymmetry from two aspects of quality signal and intention signal and comprehensively elaborates on the application of dynamic signal in the crowdsourcing field.

5.2. Practical Significance

The findings of this paper have important practical implications for the seeker. First, among the stimuli of sequential effects, the primacy effect is more influential than the recency effect for high-quality solvers, so value-added services such as project topping are ineffective in attracting high-quality solvers in projects of a short period. The analysis of the dynamic signaling model constructed in the process stage reveals that the project location is positively correlated with the participation behavior of high-quality solvers. That is, as the project location is pushed back, the newly emerged projects do not quickly overwrite the original projects. The main reasons may be as follows: (1) the location of the data obtained in this paper is mainly concentrated in the first three pages, and the location advantage may not be obviously demonstrated. (2) The design and submission of solutions for creative projects take a certain amount of time. Solvers with stronger expertise tend to spend more time on projects and are more likely to deliver more and higher-quality solutions. Just like the research of Majchrzak et al. [49], they believe that the crowd does not follow a simple recent focus, and people will interpret changes in the environment differently based on their own knowledge and experience. A truly accepted solution should have experienced overlapping, modification and improvement of knowledge. Therefore, although the project location changes over time, it does not have a significant negative impact on high-quality solvers. For value-added services such as project topping introduced by the crowdsourcing platform, the seeker may not consider for a limited period, which can effectively reduce the actual cost of the seeker.

Second, a project with a longer period and relatively higher prizes can attract more high-quality solvers within a limited time. To reach sufficient scale, crowdsourcing contests need to last long enough to attract the attention of solvers, especially innovative projects. Sufficient time allows the solver to modify and iterate ideas. However, if the project takes too long, it will increase the cost of project management and may lose public attention [65]. The project period in this paper is more than 80% within 10 days, and the average project period is less than 7 days. The platform also gives the reference of the project period in 7–10 days, so try to increase the length within a reasonable time period, which can give more time for design and creation, and can attract more high-quality solvers to participate.

Third, the existence of multiple projects on the same platform at the same time makes the projects compete with each other. The intention of the solver to participate is to obtain the prize, so the project with a relatively higher prize in the same type and time period can attract more high-quality solvers to participate. The seeker can consider assessing the difficulty of the project within a reasonable project period, offering a relatively high prize to directly obtain a satisfactory solution. They can consider adding the amount of value-added services purchased to the initial project prize directly to improve the competitiveness of the project.

Fourth, competition within the project and outside the market have different impacts on high-quality solvers. Therefore, the impact of different competitions should be considered separately. The findings show that more views and more submissions lead to fewer high-quality solvers, and the distribution of solvers is not fixed and is influenced by the external environment. As found in this paper, market competition shows a U-shaped effect as the solvers' rating rises, indicating that the quality distribution of solvers is not fixed. Therefore, it is biased to proxy the number of solvers for crowdsourcing performance in creative projects [16]. The seeker should still focus on how to communicate effectively with high-quality solvers to reduce the information asymmetry between the two parties and attract the participation of high-quality solvers. For example, the seeker can judge

the ability of the solver through personal tags, reputation, and other signals, filter out low-quality solvers in advance, and avoid wasting too many resources when evaluating a large number of solutions.

Finally, project titles and details also have an important impact on solver behavior. Details are the key to launching a crowdsourcing project. The seeker expresses its needs through project details, and the solver uses the details to infer the seeker's ideas. A survey of microtask crowdsourcing found that poor, vague task details are a significant barrier to completing tasks. Currently, the framework design of crowdsourcing projects has received more attention, and there have been studies exploring the impact of language features on the participation of solvers [66]. In the early stages of a project, accurate language signals can reduce information asymmetry and convey the intention of the seeker, thereby attracting more solvers to participate [58]. Therefore, when designing a project, requirements should be as detailed and accurate as possible, avoiding conceptual and vague words, and specific references can be given by providing examples. In addition, during the project process, the seeker can consider using feedback signals for real-time communication to obtain high-quality solutions as soon as possible.

5.3. Limitations and Future Research Directions

This paper has some limitations and provides ideas for future research. First, although the Winvk platform is one of the largest crowdsourcing platforms in China, the market competition and the number of high-quality solvers involved in the research are limited to this platform. However, the entire crowdsourcing market includes multiple platforms, and solvers can participate in different platforms projects, leading to competition among different platforms. The research fails to capture changes in the overall labor market. In order to reduce the impact of different platforms, we can try to select logo design projects from multiple crowdsourcing platforms within the same time period for comparative analysis. In order to make the results of the comparative analysis more convincing, multiple time periods can be selected for repeated verification to support the research conclusions of this paper.

Second, although the research takes into account the dynamic changes in the competition market, the changes are recorded at a 24 h interval. In reality, the market is changing all the time, with projects starting or solvers joining at every moment. The accuracy of the measurement methods can be further improved to bring the research process closer to reality. For example, data are collected at intervals of 1 h, 3 h, and 6 h, and empirical analysis is conducted on the collected data to discover the more detailed influence process of signal factors.

Finally, this paper only considers one category of creative design; however, the impact of information asymmetry on different category projects is not exactly the same. In order to verify the generalizability of the research results of this paper, we can consider extending the research to different types of projects in the future. For example, we can collect data from multiple categories such as website design, program development, and marketing copywriting to conduct a larger and more in-depth exploration of the application of signal theory.

6. Conclusions

Although previous studies have focused on the relationship between quantity and quality in the field of crowdsourcing, the studies have concentrated more on the impact on the quantity of the solvers, which is a reflection of quality according to the implications of the extreme value theorem. In addition, to obtain satisfactory solutions quickly and efficiently, most previous studies have been limited to cost-effectiveness and have not taken into account the impact of information asymmetry. To address the above issues, we construct a dynamic model based on quality signals, and intention signals to explore the information signals affecting the participation of high-quality solvers. The research results show that clear information display and incentive mechanisms have a positive impact on promoting the participation of high-quality solvers, but project competition and market

competition hinder the further participation of high-quality solvers. This paper helps to explain how to better attract high-quality solvers and reduce information asymmetry between solvers and seekers from both theoretical and practical aspects. Despite the limitations of the current study, this study provides suggestions for sustainable development in the crowdsourcing field and provides a basis for further exploration in reducing information asymmetry to attract high-quality solvers.

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