"MATTHEW EFFECT" OR "COGNITIVE FIXATION"? THE ROLE OF PAST SUCCESS EXPERIENCE IN CROWDSOURCING CONTESTS

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ABSTRACT

Understanding the mechanisms underlying participants' performance in crowdsourcing contests is a critical issue for practitioners to extract maximum value from crowdsourcing contests. However, as a vital factor, research on the role of past successful experience in crowdsourcing contests lacks consistent conclusions and further analysis of its specific factors. Using data collected from Epek.com, we bring together two disparate but related streams of literature and provide a novice understanding of the complicated, non-linear relationship between past successful experience and future performance. Then, we use text mining to capture the specific factors of tasks and experience and verify their moderating effects. The results show that the solver's success experience has an inverted U-shaped relationship with future performance in crowdsourcing contests. There is a weaker inverted U-shaped relationship when the solver's experience is more diverse or their past success experience is more similar to the current crowdsourcing task. The implications of our findings for researchers and practitioners are discussed as well.

Keywords: Crowdsourcing contest; Past success experience; Future performance

1. Introduction

Crowdsourcing contests, as one of four typical forms of crowdsourcing applications (including contests, collaborative communities, complementors, and labor markets) [Boudreau & Lakhani 2013], are where the seeker posts a well-defined problem and then evaluates solutions from solvers who wish to participate in the crowdsourcing platform; finally, the winner, selected by the seeker, can receive a fixed sum of prize money [Terwiesch & Xu 2008; Archak 2010; Liu et al. 2014; Huang et al. 2012; Zhang et al. 2019; Mo et al. 2019]. According to the state of crowdsourcing in 2017 [Eyeka 2017], brands involve the crowd at many stages of the creative process, from innovation to communications and content creation. In addition, 85% of the best global brands had used crowdsourcing by 2014 [Roth 2015], and crowdsourcing is projected to have sustained growth. Many studies have shown that crowdsourcing contests have the advantages of being low cost and high quality [Buhrmester et al. 2011] and provide easy access to a large, stable, and diverse subject pool [Mason & Suri 2012] as well as high levels of

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novelty and customer benefit [Poetz & Schreier 2012]. Therefore, crowdsourcing contests are currently receiving increasing attention from researchers and practitioners.

The mechanism of the crowdsourcing contest provides seekers a large-sized and diverse pool of solvers, resulting in a much better solution than via traditional ways. Due to the limited number of winners in a crowdsourcing contest, however, many solvers whose solutions were not selected by the seeker incur the cost of failure by themselves [Guo et al. 2017; Zhang et al. 2019]. Hence, to extract maximum value from a crowdsourcing contest, it is vital for practitioners and researchers to understand the mechanisms underlying solvers' chances of winning [Yang et al. 2011; Bayus 2013; Bockstedt et al. 2016; Mo et al. 2019]. Theoretically, in a crowdsourcing contest, solvers' chances of winning should be tightly linked to the quality of their solutions. However, some research has also shown that the likelihood of success cannot be fully explained by the solution's quality but is also partly due to solvers' submission behaviors, such as the submission sequence [Yang et al. 2011], the number of submissions [Bockstedt et al. 2015], and the length of active participation [Bockstedt et al. 2016].

Most recently, historical experience has been further identified as an essential factor in attracting the researcher's attention and affecting the chances of solvers' winning in crowdsourcing contests [Yang et al. 2011; Bayus 2013; Mo et al. 2019]. Two competing opinions on this finding may be distilled from previous social-scientific literature—what is called the "Matthew effect" and "cognitive fixation." The Matthew effect refers to the "rich get richer" principle, that is, according to the human capital theory, those who have more past success experience have an easier time gaining even more successful wins in later tasks [Azoulay et al. 2014; Yang et al. 2011; Merton 1968]. What drives the Matthew effect in crowdsourcing contests is that solvers can employ more declarative knowledge, procedural knowledge, and skills from past success experience, which bring more opportunities for creating a high-quality solution and lead to successful wins in later tasks [Yang et al. 2011; Mo et al. 2019]. Nevertheless, recent research has found that historical success does not always yield benefits and may sometimes give rise to negative performance consequences based on the cognitive psychology theory [Bayus 2013]. That is, too much experience may limit the use of knowledge and heuristics in the ideation process, and solvers with vast success experience are much more likely to form cognitive fixations that will result in lower performance in future tasks, especially in ideation ones [Bayus 2013; Jansson & Smith 1991].

To gain insight into which of these processes most strongly acts on the chances of winning in crowdsourcing contests, our goal is to clarify the following main research question: (1) How does solvers' past success experience affect their chance of winning in crowdsourcing contests? According to the too-much-of-a-good-thing (TMGT) effect suggested by Pierce and Aguinis [2013], management researchers should hypothesize and test the possibility that relatively high levels of otherwise beneficial antecedents may lead to unexpected and undesired outcomes. This work draws on this idea and integrates the seemingly opposing arguments of the "Matthew effect" and "cognitive fixation" views by postulating a previously untested inverted curvilinear relationship between solvers' past success experience and their chance of winning in a crowdsourcing contest. Initially, experience accumulation enables solvers to develop wisdom, in-depth knowledge, and the ability to respond to situations [Littlepage & Mueller 1997], allowing them to exploit routines to cope with problems [Huckman et al. 2009] and thereby improving their future performance on other crowdsourcing tasks. After a certain threshold, however, too much success experience is negatively impacted by cognitive fixations, limiting the innovation of solutions, which is the key to winning the crowdsourcing contests. At this threshold, the marginal utility of the benefits brought about by historical experience growth is lower than the disadvantage caused by the cognitive fixation. The inhibition from cognitive fixation starts to outweigh the benefits of accumulating additional related knowledge and skills from past success experience, progressively leading to a relative lack of innovative and competitive solutions, which reduces the chance of winning in future crowdsourcing contests.

Further, experience is a complicated factor, involving more than just the number of successes [Mo et al. 2018]. Solvers who have had the same number of past successes may have different results in current crowdsourcing contests due to the different characteristics of the solvers' experience and the current crowdsourcing tasks [Unger et al. 2011; Kohn & Smith 2011; Schilling et al. 2003; Sturman 2003; Sivatte et al. 2019]. Therefore, we identify two experience-related factors and one task-related factor as potential moderators. The experience-related factors include the experience diversity and the similarity between the experience and the current task. The former reflects the breadth of experience, while the latter mirrors the different matching levels of experience and tasks. Both dimensions of experience characteristics have been proven to affect the transfer process of the knowledge and skills and have effects on the impact mechanism of cognitive fixation on innovation performance [Cohen & Levinthal 1990; Hinsz et al. 1997; Kohn & Smith 2011; Bayus 2013]. In addition, the task-related factor we selected is task complexity, which has been found to moderate the relationship between job experience and performance [McDaniel et al. 1988; Sturman 2003; Sivatte et al. 2019]. For this reason, in order to explore the situational effects of the influence of solvers' past experience on their future performance in crowdsourcing contests from the characteristics of solvers' experience and the current tasks, we focus on the following two questions: (2) Does task complexity moderate the relationship between a solver's past experience and the chance of winning? (3) Is the relationship between a solver's past experience and the chance of winning moderated by the solver's experience characteristics, including experience diversity and similarity between previous experience and the current task?

This study makes several contributions to research and practice. First, we combine the two contradictory research streams and break through the inherent assumptions of a linear relationship in the existing research and construct a curvilinear relationship hypothesis between experience and future performance; thereby, the study allows us to gain a more nuanced view of the role of past success experience in crowdsourcing contests. Second, to our knowledge, the current study is also the first to use text mining in capturing the characteristic factors of tasks and experience to shed new light on the relationship between crowdsourcing experience and future performance. Furthermore, the implications of our results can help solvers to effectively use their historical success experience to improve their odds of winning in future crowdsourcing tasks and achieve sustainable development. Our study also provides helpful insights for seekers in forming a more comprehensive and reliable evaluation of potential solvers. Finally, our findings provide valuable insights into how crowdsourcing platform managers should formulate tasks and solver recommendation mechanisms to improve their operational efficiency.

The remainder of this article is structured as follows. We first present the literature and theoretical background and construct a research model and hypotheses in Section 2. Next, we describe the data and research methodology in Section 3. Then, we report the empirical results and our main findings in Section 4. In Section 5, we summarize the theoretical and managerial implications of the findings and present conclusions. Finally, we discuss the limitations and offer suggestions for future research.

2. Theoretical Background and Hypotheses

In this section, we propose the research model depicted in Figure 1. The aim of this model is to understand the relationship between solvers' past success experience and their performance in crowdsourcing contests. Moreover, we explore how the relationship is moderated by solvers' experience characteristics (i.e., diversity of past experience and similarity between solvers' success experience and the current task) and task complexity. In the following sections, we discuss the key components and the relationships shown in the proposed model.

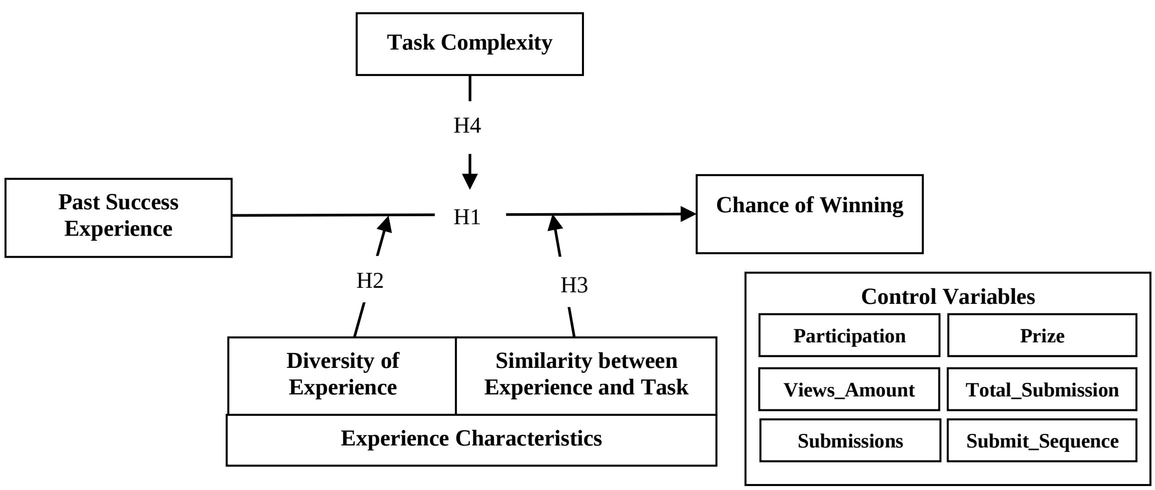


Figure 1: Research Model

2.1. Solvers' Performance in Crowdsourcing Contests

To better play the value of crowdsourcing contests on open innovation, it is vital for practitioners and researchers to study the influence mechanisms of solvers' performance [Mo et al. 2019]. Performance is defined as goal-relevant actions that are under the control of the individual [Campbell et al. 1993]. In a crowdsourcing context, the probability of a solver winning a contest is often used to scale the solver's performance [Yang et al. 2011; Bayus 2013; Bockstedt et al. 2016; Mo et al. 2019]. The existing literature has identified different factors influencing solvers' performance in crowdsourcing contests from several aspects, as follows: the design mechanisms of the contest itself, solvers' submission behaviors during contests, and factors related to solvers' attributes. The characteristics of contest design mechanisms studied previously include reward settings [Liu et al. 2014; Zheng et al. 2014], prize guarantees [Jian et al. 2019], the interaction between seekers and solvers [Zheng et al. .2014], solution visibility [Boudreau & Lakhani 2015], the feedback and sharing policies regarding solutions [Lee et al. 2018; Jian et al. 2019], and the competition intensity of tasks [Boudreau et al. 2011; Mo et al. 2019]. Others have studied how solvers' performance is affected by their submission behaviors during contests, such as submission sequence [Yang et al. 2011], the number of submissions [Bockstedt et al. 2015], and the length of active participation [Bockstedt et al. 2016]. At the individual level, researchers have analyzed the role of solvers' ability [Terwiesch & Xu 2008; Dechenaux et al. 2015], past success experience [Yang et al. 2011; Bayus 2013], knowledge diversity [Lee et al. 2015], intrinsic motivators [Frey et al. 2011], cooperation orientation [Bullinger et al. 2010], and sharing of online profiles [Ren et al. 2019]. Particularly, as a critical factor affecting crowdsourcing performance, past success experience has received the attention of existing research. However, due to prior studies focusing solely on a single theoretical perspective, no consistent research conclusion has been obtained thus far. More importantly, previous related studies have considered only the volume of past success experience and neglected its characteristics, such as diversity and similarity to the current task. Therefore, it is essential to understand the influence mechanisms of past success experience and its characteristics to nurture better performance in crowdsourcing contests.

2.2. Past Success Experience and Performance in Crowdsourcing Contests

According to the traditional human capital theory, experience is an essential aspect of human capital, raising workers' knowledge and skills and leading to increased performance [Becker 1962; Schmidt et al. 1986]. We suggest that solvers' past success experience is associated with increased their future performance in crowdsourcing contests because it helps solvers to improve their knowledge and skills. There are two reasons for this. First, past experience provides the opportunity for individuals to acquire relevant knowledge and skills that can, in turn, enhance performance on the job [Borman et al. 1993]. Hence, much of the related research has proven that experience can be a good indicator of future performance and found a positive relationship between prior experience and future performance [Avolio et al. 1990; Hunter & Hunter 1984; McDaniel et al. 1988; McEnrue 1988; Quinones et al. 1995; Sturman 2003; Mo et al. 2018]. Second, past experience leads individuals to develop wisdom, in-depth knowledge, and the ability to respond to situations [Littlepage & Mueller 1997] and allows individuals to develop routines to solve problems [Huckman et al. 2009]. Under the environment of a crowdsourcing contest, veteran solvers become more proficient as they gain experience, and this can help them become more adept at executing existing routines, improving their future performance on other tasks [Archak 2010; Boudreau et al. 2011; Yang et al. 2009; Mo et al. 2018].

However, too much experience can also be detrimental to future ideation efforts, and the pervasive impediment to acquiring knowledge and skills from prior relevant experience is cognitive fixation [Jansson & Smith 1991; Smith 1993; Cardoso & Badke-Schaub 2011]. Research on cognitive fixation suggests that past experience may limit the knowledge and heuristics used in the ideation process, leading to lower performance on future tasks, especially ideation ones [Birch & Rabinowitz 1951; Jansson & Smith 1991]. In practice, idea crowdsourcing had accounted for more than 68% of publicly available contests by 2016 and has maintained rapid growth [Eyeka 2017], thus the negative effects from cognitive fixation may be even more critical in the current crowdsourcing context. Moreover, the negative effects of too much experience are also explained by the idea of competency traps or core rigidities [Levitt & March 1988; Leonard-Barton 1992]. These show that individuals may become fixed in their way of doing things and that, as conditions change, they will not respond to the changing conditions [Huckman et al. 2009].

More importantly, Pierce and Aguinis [2013] posited their TMGT framework and stipulated that "good things," such as past experience, reach inflection points after which their association with the performance or other positive outcomes turn negative. Based on this, some studies have generated an inverted U-shaped relationship between past experience and future performance, whereby increasing historical experience is first related to improved future performance and later associated with the deterioration of future performance. [Staw 1980; Kc & Staats 2011; Sivatte et al. 2019; Mueller et al. 2020]. Integrating these arguments, we expect that past success experience will have an inverted U-shaped relationship with solvers' chances of winning in crowdsourcing contests. That is, successful past experience can help solvers build confidence and acquire relevant necessary knowledge and skills, thereby increasing the likelihood of future success. For these reasons, past success experience should increase the probability of future success but only up to a certain point. Having too much experience may become a liability because of its association with cognitive fixation, which will have a negative impact on future innovation performance. For solvers with too much experience, greater cognitive fixations offset the positive effects of having more relevant knowledge and skills on future performance. In other words, such solvers will become increasingly less able to use their experience in an efficient and innovative way, which is very important in the crowdsourcing contest context [Bayus 2013].

Taken together, we propose the following hypothesis:

H1: *During a crowdsourcing contest, a solver's past successful experience has an inverted U-shaped relationship to their chance of winning with the current submission.*

2.3. The Moderating Effects of Solvers' Experience Characteristics

As experience is a complicated factor that involves more than just the number of successes, solvers who have had the same number of wins in past crowdsourcing contests may have different results due to the diversity of their experience or the similarity between their past success and the current task. Thus, the relation between solvers' past experience and the chance of winning in crowdsourcing contests may be dependent on certain moderators based on the characteristics of the solver's experience. To explore the mechanisms underlying the influence of solvers' past experience on their future performance in crowdsourcing contests, we identify two experience-related factors as potential moderators, namely, experience diversity and similarity between experience and task.

Since the crowdsourcing contest platform contains multiple categories of tasks, solvers can participate in tasks in different areas to gain more comprehensive experience than in the traditional work environment. Diversity reflects the breadth of experience and has been shown to have a positive impact on learning and, therefore, can influence future performance [Cohen & Levinthal 1990]. Schilling et al. [2003] pointed out that experience in a problem domain can provide analogous solutions in a new one and that the diversity of experience can improve the capacity to transfer knowledge across areas [Cohen & Levinthal 1990]. However, in the initial stage, the more diverse the solver's participation experience is, the more sluggish the effective knowledge and skills accumulation is in regard to any type of tasks in a crowdsourcing platform, resulting in a slower ascent to the top (i.e., the upward side of the inverted U-shaped relationship will flatten when the solver's past success experiences are of greater diversity). In contrast, diverse experience, according to cognitive psychology theory, can minimize the negative effects of cognitive fixation [Hinsz et al. 1997; Kohn & Smith 2011; Bayus 2013]. Those with less varied or even single category experience are more likely to be constrained by certain mindsets, which exacerbates the negative impact of experience on future innovation performance in crowdsourcing contests. Specifically, solvers who have engaged in more varied types of crowdsourcing tasks have more flexible thinking. Thus, cognitive fixation has a weaker negative effect on these solvers, resulting in a slower descent from the top (i.e., the downward side of the inverted U-shaped relationship will flatten when the solver's past success experiences are more diverse).

Hence, we argue that experience diversity moderates the relationship between past experience and chance of winning in crowdsourcing contests and propose a second hypothesis, as follows:

H2: *Diversity of past experience negatively moderates the inverted U-shaped relationship between solvers' past experience and their chances of winning in crowdsourcing contests.*

The similarity between solvers' past experience and the current task is an experience-related context variable that may influence the relationship between solvers' experience and their chances of winning in crowdsourcing contests as the effectiveness of experience in helping knowledge transfer differs across the different matching levels of experience and tasks. Unger et al. [2011] stated that the effect of experience, as one of the most critical forms of human capital, on future performance is strongest when the experience is task-related. From the learning and knowledge perspective, it is easier for individuals to transfer skills or knowledge from prior tasks to other similar tasks [Narayanan et al. 2009]. As similar knowledge and skills are needed to complete the task or solve the problem, knowledge and skills from prior experience are more likely to be transferred successfully when there are structural similarities between past experience and the current task [Singley & Anderson 1989]. In the initial stage, which focuses on accumulated knowledge and skills, the past successful experience of the solver is more similar to the current task, which can bring more relevant knowledge and skills to better complete the task. However, on this basis, as the new knowledge and skills brought by additional similar experience are relatively less, the marginal utility increased by relevant experience is relatively low; that is, in more similar cases, the slope of the rising stage is lower. In contrast, the more similar the past successful experience is to the current task, the deeper the understanding of the task domain will be [Schilling et al. 2003]. Therefore, when the current task is more similar to one's historical success experience, the success experience can bring more practical knowledge and skill accumulation, which can be more easily transferred to the solution of the current task, and the negative impact brought by cognitive fixation can be weakened. Consequently, when the solver's past successes are more similar to the current task, the downward side of the inverted U-shape will flatten out.

So, we put forward the following hypothesis:

H3: *Similarity between solvers' success experience and the current task negatively moderates the inverted U-shaped relationship between solvers' past experience and their chances of winning in crowdsourcing contests.*

2.4. The Moderating Effects of Task Complexity

According to job performance theory, complexity is defined as the extent to which a job entails autonomy and allows for decision latitude [Kohn & Schooler 1983], and it has been found to moderate the relationship between job experience and performance [McDaniel et al. 1988; Sturman 2003; Sivatte et al. 2019]. For instance, Sivatte et al. [2019] found that prior experience has a more muted influence on job performance of high complexity than low-complexity jobs. Complex tasks will make it harder to acquire the knowledge and skills required for the job and make it harder to match with a suitable task from prior experience [Sturman 2003]. In the crowdsourcing contest context, complex tasks may have multifaceted requirements, necessitating more intricate thought processes to transfer knowledge and skills from past experience than do simpler ones [Mo et al. 2018]. Hence, we argue that task complexity can influence the application of knowledge and skills from experience and acts as a moderating factor between solvers' past experience and their chances of winning in crowdsourcing contests.

However, the multifaceted requirements of such a complex task are more difficult to be negatively affected by cognitive fixation and other factors. For example, Sturman [2003] and Sivatte et al. [2019] found that the inverted U-shaped relationship between work experience and job performance held for low-complexity jobs. In highly complex jobs, the relationship was positive. In other words, the negative effects of experience at later stages increased more rapidly in low-complexity tasks.

Thus, we posit the following hypothesis:

H4: *Task complexity negatively moderates the inverted U-shaped relationship between solvers' past experience and their chances of winning in crowdsourcing contests.*

3. Research Methodology

This study used detailed data from a Chinese crowdsourcing contest platform to examine the proposed hypothetical model. This section will introduce the data collection process, variable selection, and the empirical model's construction.

3.1. Data

Epek.com (www.epwk.com) provides an ideal research context in which to investigate our research questions. Epek.com was founded in 2010 and is one of the most popular crowdsourcing contest platforms in China. The types of crowdsourcing tasks provided by Epek.com cover more than 300 items in the following seven categories: design, development, decoration, copywriting, marketing, business, and virtual reality (VR). This allows us to observe solvers' experience in a wide variety of contexts, and it avoids any industry biases. As of June 2019, Epek.com had over 19 million registered users, and its accumulated transaction value exceeds RMB 17 billion [Epwk.com 2019].

To test the above hypotheses, in this research, we developed a crawler to collect data from Epek.com. Data collection started from the task listing page, which provides all completed tasks. For each such task, it then went to the task details page and collected all the information available there, including task title, task ID, task requirement, task award, post time, number of submissions, and the winner. The crawler then visited the corresponding solution page to collect information on all solutions, including the list of submissions with the submission time and submission ID of each solution. Finally, it collected all available information on each participating solver, including solver ID, times of past wins, historical turnover, the score of satisfaction, and all available information on their previous successful tasks. The data collection was conducted in November 2019. We collected completed tasks in all seven categories that had been posted between November 2016 and October 2019. Since our goal is to analyze the role of past successful experience in crowdsourcing contests, the sample contains only submissions of those who have had at least one success experience. The total sample size in this study is 48,890 submissions from 647 solvers. We then removed 98 submissions from solvers who had participated in only one crowdsourcing task because these one-time solvers do not have any past winning experience and thus cannot be motivated by a prior success [Bayus 2013]. The final sample contains 48,792 submissions from 547 solvers who have had at least one successful experience.

3.2. Measures

3.2.1. Dependent Variable

In the research model, we investigate whether past success experience influences the likelihood of a successful submission. To do so, we create a binary variable where a value of one indicates that the submission was chosen by the seeker (otherwise zero). Notably, the dependent variable we created is objective and publicly available from the Epek.com website. Of note, many related studies have used variables similar to ours [Bayus 2013; Bockstedt et al. 2016; Mo et al. 2019].

3.2.2. Independent Variable

To measure past success experience, we count the cumulative number of past submissions that were successfully selected by seekers before the solver submitted the current submission. On Epek.com, we can access a solver's historical participation records and count their winning situations by visiting their personal homepage.

3.2.3. Moderating Variables

The diversity of solvers' past experience, the similarity between prior success experience and the current task, and task complexity are treated as moderating variables in our study. To measure these moderating variables, the text-similarity of task requirements between the current task and each task the solver previously participated in is calculated first. We use our proposed text similarity measurement algorithm to calculate these text similarities, detailed as follows.

Firstly, following existing studies about the similarity measurement of text [Mohammad et al. 2017; Nanda et al. 2019; Zhou et al. 2020], we use the term frequency-inverse document frequency (TF-IDF) to calculate the frequencies of each word in a task requirement text and in the entire text set. This method measures the value of each word in a task requirement text by using an inverse proportion of word frequency in a specific task requirement text to the percentage of texts in which the word appears to measure the value of each word in a task requirement text [Qaiser & Ali 2018; Yahav et al. 2019; Zhou et al. 2020]. The calculation process of the TF-IDF value of each word can be written as

$$TF\text{-}IDF_{ij} = \frac{f_{ij}}{\sum_k f_{kj}} \cdot \log \frac{|D|}{1 + \left|\{ j : word_i \in t_j \}\right|} ,$$

where f_{ij} is the appearing frequency of $word_i$ in task requirement text t_j, $|D|$ represents the total number of files in the corpus, and $\left|\{ j : word_i \in t_j \}\right|$ denotes the number of texts containing the $word_i$.

Secondly, we transfer each text as a vector using the TF-IDF values we calculated. As such, each task requirement text t_j is mapped to a feature vector of the vector space:

$$t_j = (w_1, TF\text{-}IDF_{1j}; w_2, TF\text{-}IDF_{2j}; \cdots ; w_m, TF\text{-}IDF_{mj}) ,$$

where w_m is the featured item of the task requirement text t_j, and $TF\text{-}IDF_{1j}$ represents the weight corresponding (measured by TF-IDF value) to the featured item.

Finally, following Gomaa and Fahmy [2013] and Zhou et al. [2020], we use the cosine of similarity between vectors to represent the text-similarity of task requirements between the current crowdsourcing task and each past task in which the solver participated. The mathematical definition can be written as

$$Similarity(t_0, t_j) = \cos(\theta_j) = \frac{t_0 \cdot t_j}{\|t_0\| \times \|t_j\|} ,$$

where t_0 is the vector of the current task requirement, and t_j denotes the vector of task requirement text t_j.

The diversity of a solver's past experience is defined as the degree of difference in task requirements between participating crowdsourcing projects; the more the change of similarity between the current task and each past task, the higher the diversity of a solver's past experience. So, we use the standard deviation of text similarity between the current task and each past task the solver participated in, measuring the diversity of the solver's past experience. The mathematical definition can be written as

$$Diversity = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (Similarity(t_0, t_i) - \mu)} ,$$

where t_0 is the current task requirement text, and t_i represents the task requirement text of each past task the solver participated in before taking part in the current task. N denotes the total number of submissions before participating in the current crowdsourcing contest.

The similarity between prior success experience and the current task indicates the similarity between the current task and successful historical experience. We use the average similarity between the current task and the successful historical tasks to calculate this variable. The mathematical definition can be written as

$$Ave\_Similarity = \frac{\sum_{i=1}^{n} Similarity(t_0, t_i)}{n} ,$$

where t_0 is the current task requirement text, and t_i represents the task requirement text of each past successful task the solver participated in before taking part in the current task. N denotes the cumulative number of past submissions selected by seekers successfully before the solver's current submission.

Finally, we use the number of feature items of the task requirement text to measure task complexity. The more the item featured in the task requirement text, the more complex the crowdsourcing task.

3.2.4. Control Variables

To mitigate the omitted variable bias and the resulting endogeneity concern, we include an extensive set of control variables that may be associated with solvers' chances of winning in crowdsourcing contests, including solvers' characteristics, solvers' submission behaviors, and tasks' characteristics. Scholars have suggested that these factors may influence solvers' chances of winning in crowdsourcing contests [Terwiesch & Xu 2008; Yang et al. 2011; Bayus 2013; Bockstedt et al. 2016; Mo et al. 2019]. Therefore, to better understand the effects of solvers' past experience in the proposed research model, we utilize these factors as a series of control variables affecting solvers' chances of winning in crowdsourcing contests.

First, we control for the solver's general participation experience because it has been found by many scholars to influence performance in crowdsourcing contests [Yang et al. 2009; Archak 2010; Boudreau et al. 2011; Mo et al. 2019]. In keeping with prior research [Archak 2010; Mo et al. 2019], we measure the solver's general participation experience by the total number of tasks participated in before the solver submitted a solution in the current crowdsourcing task.

Second, we control for certain variables related to solvers' submission behaviors in the current crowdsourcing task, including *Submit_Sequence* (order of the submission in all submissions of the current task) and the number of *submissions* (number the current solver submitted in the current task) [Bockstedt et al. 2015; Bockstedt et al. 2016].

Finally, we include control variables relating to tasks' characteristics, such as *Prize*, *Views_Amount*, and *Total_Submissions* (total number of submissions in the current crowdsourcing task) [Terwiesch & Xu 2008; Yang et al. 2011; Bayus 2013; Mo et al. 2019].

A detailed description of all of the variables included in this study is summarized in Table 1.

Table 1: Description of Variables

Type	Variable	Definitions
Dependent variable	*Chance_of_Winning*	= 1 if the submission won the current contest (0 otherwise)
Independent variable	*Succeed_Expierience*	The number of wins before the solver submitted the current solution
Moderating variable	*Diversity*	The standard deviation of text similarity between the current task and each past task the solver participated in
	Ave_Similarity	The average similarity between the current task and successful historical tasks
	Complexity	The number of feature item of the task requirement text
Control variable	*Participation*	The total number of tasks participated in before the solver submitted a solution in the current task
	Prize	The prize of the current task
	Views_Amount	The number of views of the current task
	Total_Submissions	The total number of submissions in the current crowdsourcing task
	Submit_Sequence	The order of the submission in all submissions of the current task
	Submissions	The number the current solver submitted in the current task

3.3. Empirical Model

Since our dependent variable is dichotomous, a logit model is preferred over an ordinary least squares (OLS) model [Pindyck & Rubinfeld 2012]. OLS is subject to certain problems in probabilistic models, including the non-normal distribution of error terms, the heteroscedastic variance of error terms, estimated probabilities being more significant than 1 or lower than 0, and R_2 being very low [Gujarati 2009]. Moreover, the logit model does not assume homoscedasticity and has fewer restrictive requirements compared to the simple linear regression model [Batool et al. 2019]. Meanwhile, the correction of bias is easy with the logit model as it is not very sensitive to outliers compared to the probit model. Hence, in this study, we use the logit model to examine our research model and hypothesis.

The generalized form of cumulative logistic function can be written as

$$P_i = E(Y=1 \mid X_i) = \frac{1}{1+e^{-z_i}}, Z_i = \alpha + \beta X_i ,$$

where X_i represents the vector of independent variables, and P_i gives us information about independent variables and shows us the probability of being successful in crowdsourcing contests. By using the variables mentioned above, in order to test H1, a hierarchical regression analysis was conducted. The first model includes only control variables and moderating variables. Then, to test the main effect of the independent variable, the linear variable was entered into the second model and the quadratic term into the third model.

Model 1 (including only control variables and moderating variables):

$$\text{Chance\_of\_Winning} = \ln(\frac{P}{1-P}) = \alpha + \beta_X X + u$$

Model 2 (add independent variable):

$$\text{Chance\_of\_Winning} = \ln(\frac{P}{1-P}) = \alpha + \beta_1 \text{Ln\_Succeed\_Expierience} + \beta_X X + u$$

Model 3 (add independent variable's quadratic term):

$$\text{Chance\_of\_Winning} = \ln(\frac{P}{1-P}) = \alpha + \beta_1 \text{Ln\_Succeed\_Expierience} + \beta_2 (\text{Ln\_Succeed\_Expierience})^2 + \beta_X X + u \text{，}$$

where α is the intercept term, β_1, β_2 are the regression coefficients of independent variables, X is a vector of control variables and moderating variables, β_X is a vector of the regression coefficients of control variables and moderating variables, and u is the stochastic error term.

To estimate the moderating effect of moderating variables on the U-shaped relationship between the solver's success experience and their chance of winning, we also include interaction items between each moderating variable and independent variable (both its quadratic term and itself) in Models 4–6. Moreover, motivated by Balli [2013], the interactions were mean-centered to overcome potential problems arising from multicollinearity.

Model 4:

$$\text{Chance\_of\_Winning} = \ln(\frac{P}{1-P}) = \alpha + \beta_1 Ln\_Succeed\_Expierience + \beta_2 (Ln\_Succeed\_Expierience)^2$$
$$+ \beta_3 Ln\_Succeed\_Expierience \times Diversity + \beta_4 (Ln\_Succeed\_Expierience)^2 \times Diversity + \beta_X X + u$$

Model 5:

$$\text{Chance\_of\_Winning} = \ln(\frac{P}{1-P}) = \alpha + \beta_1 Ln\_Succeed\_Expierience + \beta_2 (Ln\_Succeed\_Expierience)^2$$
$$+ \beta_3 Ln\_Succeed\_Expierience \times Avg\_Similarity + \beta_4 (Ln\_Succeed\_Expierience)^2 \times Avg\_Similarity + \beta_X X + u$$

Model 6:

$$\text{Chance\_of\_Winning} = \ln(\frac{P}{1-P}) = \alpha + \beta_1 Ln\_Succeed\_Expierience + \beta_2 (Ln\_Succeed\_Expierience)^2 \quad ,$$
$$+ \beta_3 Ln\_Succeed\_Expierience \times Complexity + \beta_4 (Ln\_Succeed\_Expierience)^2 \times Complexity + \beta_X X + u$$

where α is the intercept term, β_1, β_2 are the regression coefficients of independent variables; β_3, β_5, β_7 are the interactions between each moderating variable and independent variable; β_4, β_6, β_8 are the interactions between each moderating variable and the quadratic term of the independent variable, all interactions are processed with mean centering, X is a vector of control variables and moderating variables, β_X is a vector of the regression coefficients of control variables and moderating variables, and u is the stochastic error term.

4. Results

This section will report the empirical results and our main findings, including descriptive analysis, the main regression analysis, and robustness checks.

4.1. Descriptive Analysis

Descriptive statistics for all the variables are shown in Table 2. Because all of the variables except *Diversity Similarity* and the dummy variables are highly skewed, their log transforms are used in the correlation matrix and the regression analysis. Table 3 provides the correlation matrix for the main variables in our study. As can be seen, all of the correlations between the two variables are small except for the correlation between *Ln_Succeed_Expierience* and *Ln_Participation* (0.79). To further formally test for multicollinearity, we calculate the variance inflation factor (VIF) values for all of the independent variables. Table 3 shows that the maximal VIF value is below 3.5, indicating that no substantial multicollinearity issue exists in the dataset [Mason & Perreault Jr 1991].

Table 2: Descriptive Statistics of Variables

Variable	Obs#	Mean	Std. Dev	Min	Max
Chance_of_Winning	48792	.042	.2	0	1
Succeed_Expierience	48792	9.48	17.981	0	146
Diversity	48792	.168	.087	.037	.682
Avg_Similarity	48792	.589	.321	0	1
Complexity	48792	59.845	38.633	4	329
Participation	48792	252.506	301.478	1	1896
Prize	48792	668.364	584.954	100	10800
Views_Amount	48792	2108.271	1750.525	265	55664
Total_Submissions	48792	84.504	69.02	2	722
Submit_Sequence	48792	20.694	14.516	1	78
Submissions	48792	1.57	.942	1	9

Table 3: Correlation Matrix and VIF Values of Main Variables (N = 48792)

	1	2	3	4	5	6	7	8	9	10	11
1	1.00										
2	-0.02***	1.00									
3	0.09***	-0.12***	1.00								
4	-0.10***	0.50***	-0.32***	1.00***							
5	0.01***	-0.01	0.34***	-0.17***	1.00						
6	-0.11***	0.79***	-0.24***	0.40***	-0.02***	1.00					
7	-0.01***	0.16***	0.01	0.03***	0.20***	0.14***	1.00				
8	-0.01**	-0.07***	-0.02***	-0.02***	0.13***	-0.11***	0.37***	1.00			
9	-0.08***	-0.18***	-0.05***	-0.05***	-0.08***	-0.14***	-0.26***	0.46***	1.00		
10	-0.09***	-0.10***	-0.01*	-0.01***	0.00	0.03***	0.10***	0.03***	0.16***	1.00***	
11	0.05***	0.21***	0.02***	-0.01***	0.05***	0.15***	-0.02***	0.02***	0.15***	0.04***	1.00
VIF		3.48	2.97	1.99	1.94	1.74	1.54	1.34	1.21	1.13	1.12

Notes: 1: *Chance_of_Winning*; 2: *Ln_Succeed_Expierience*; 3: *Diversity*; 4: *Avg_Similarity*; 5: *Ln_Complexity*; 6: *Ln_Participation*; 7: *Ln_Prize*; 8: *Ln_Views_Amount;* 9: *Ln_Total_Submissions*; 10: *Ln_Submit_Sequence*; 11: *Ln_Submissions*

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

4.2. Main Analysis

We used the statistical software package Stata14.0 to process our research models, and the results are reported in Table 4. Models 1–3 in Table 4 show the results relevant to H1. To confirm the presence of an inverted U-shaped relationship between success experience and the chance of winning in crowdsourcing contests, the two following criteria must be fulfilled: (1) the increase in variance explained by adding the quadratic term must be statistically significant, and (2) the regression coefficient of the linear succeed experience variable must be positive and the regression coefficient for squared term negative. After controlling for the effects of the control variables, as shown in Table 4, Model 3 includes the quadratic term, whereas Model 2 includes only the linear relationship between success experience and the chance of winning in crowdsourcing contests. We find that the regression coefficient of success experience is positive (β_1 = 1.38, $p < 0.01$) and that of the quadratic term is negative (β_2 = -0.17, $p < 0.01$) in Model 3. When comparing these two models, we find that the inclusion of the quadratic term significantly improves the model by observing the change of LR chi2 and pseudo R^2 values. Therefore, as proposed, there exists an inverted U-shaped relationship between success experience and the chance of winning in crowdsourcing contests. This result gives support to H1.

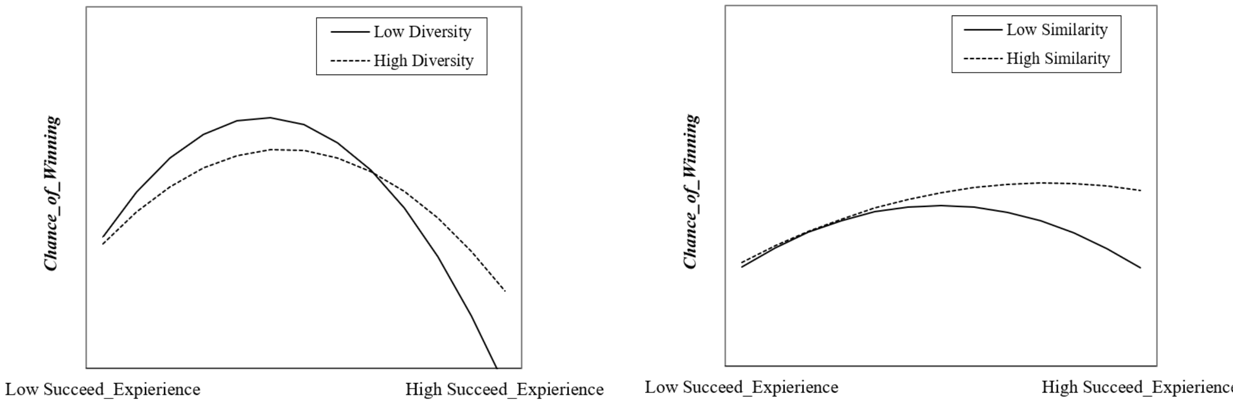
In Model 4, the coefficient of the interaction terms between experience diversity and the quadratic term of success experience is significant and positive (β_4 = 0.82, $p < 0.01$). Similarly, as shown in Model 5, the coefficient of the interaction terms between experience similarity and the quadratic term of success experience is also significant and positive (β_4 = 0.38, $p < 0.01$). These results imply that the similarity between past success experience and the current task and the diversity of the solver's prior experience both weakened the inverted U-shaped influence of success experience on the chance of winning in crowdsourcing contests. To show the adjustment effect more intuitively, we use a standard deviation above and below the moderating variables as the high and low, respectively, and draw the relationship between success experience and the chance of winning in crowdsourcing contests under different values of the moderating variables (see Figure 2). The results of Figure 2-a demonstrate that a higher level of diversity slows an upward trend in the first half of the curve and increases the threshold to reach the top. Meanwhile, the experience of high diversity mitigated the downward trend in the latter half of the curve. As can be seen from Figure 2-b, the higher the degree of similarity, the higher the starting point, and the slower the upward trend of the upper part of the curve. Meanwhile, when the past success experience is more similar to the current task, the downward trend of the latter half of the curve appears later and has a smaller slope. Therefore, H2 and H3 are supported. We will further interpret these findings in the next section.

Similar to Model 4 and Model 5, Model 6 includes the interaction terms between the task complexity and both the quadratic term and linear term of successful experience. However, the results show that the coefficients of these interaction terms are not significant. Therefore, the task complexity cannot moderate the inverted U-shaped relationship between success experience and the chance of winning in crowdsourcing contests, and H4 is not supported.

Table 4: Regressions Results of Research Model

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ln_Succeed_Expierience		0.60^{***} (0.04)	1.38^{***} (0.09)	1.79^{***} (0.10)	1.37^{***} (0.11)	1.38^{***} (0.09)
Ln_Succeed_Expierience ^2			-0.17^{***} (0.18)	-0.25^{***} (0.02)	-0.16^{***} (0.02)	-0.17^{***} (0.02)
Ln_Succeed_Expierience ×Diversity				-6.36^{***} (0.57)		
Ln_Succeed_Expierience ×Avg_Similarity					-1.04^{***} (0.24)	
Ln_Succeed_Expierience ×Ln_Complexity						0.06 (0.07)
Ln_Succeed_Expierience^2×Diversity				0.82^{***} (0.15)		
Ln_Succeed_Expierience^2×Avg_Similarity					0.38^{***} (0.06)	
Ln_Succeed_Expierience^2×Ln_Complexity						-0.03 (0.20)
Diversity	2.54^{***} (0.27)	1.34^{***} (0.28)	0.77^{***} (0.29)	1.00^{***} (0.33)	0.99^{***} (0.31)	0.80^{***} (0.29)
Avg_Similarity	-0.76^{***} (0.07)	-1.23^{***} (0.08)	-1.96^{***} (0.12)	-2.59^{***} (0.14)	-2.11^{***} (0.13)	-1.99^{***} (0.12)
Ln_Complexity	-0.15^{***} (0.04)	-0.13^{***} (0.04)	-0.16^{***} (0.37)	-0.08^{**} (0.04)	-0.15^{***} (0.04)	-0.16^{***} (0.04)
Ln_Participation	-0.20^{***} (0.02)	-0.49^{***} (0.02)	-0.54^{***} (0.02)	-0.48^{***} (0.03)	-0.54^{***} (0.02)	-0.54^{***} (0.02)
Ln_Prize	-0.20^{***} (0.04)	-0.26^{***} (0.04)	-0.27^{***} (0.04)	-0.27^{***} (0.05)	-0.28^{***} (0.04)	-0.27^{***} (0.04)
Ln_Views_Amount	0.29^{***} (0.05)	0.26^{***} (0.05)	0.27^{***} (0.06)	0.23^{***} (0.06)	0.26^{***} (0.06)	0.26^{***} (0.06)
Ln_Total_Submissions	-0.68^{***} (0.04)	-0.64^{***} (0.04)	-0.62^{***} (0.04)	-0.61^{***} (0.04)	-0.61^{***} (0.04)	-0.62^{***} (0.04)
Ln_Submit_Sequence	-0.30^{***} (0.02)	-0.21^{***} (0.02)	-0.25^{***} (0.02)	-0.25^{***} (0.02)	-0.25^{***} (0.02)	-0.25^{***} (0.02)
Ln_Submissions	0.80^{***} (0.05)	0.62^{***} (0.05)	0.64^{***} (0.05)	0.67^{***} (0.05)	0.62^{***} (0.05)	0.64^{***} (0.05)
_cons	0.62^{*} (0.35)	1.62^{***} (0.36)	1.89^{***} (0.36)	1.71^{***} (0.37)	1.99^{***} (0.38)	1.89^{***} (0.36)
LR chi2	1591.94	1862.84	1951.56	2248.00	2029.01	1958.67
Pseudo R^2	0.09	0.11	0.12	0.13	0.12	0.12
Obs#	48792	48792	48792	48792	48792	48792

Notes: Standard errors are included in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$



(a) (b)

Figure 2: Moderating Effect of Diversity and Similarity of Experience

4.3. Robustness Checks

We conducted several additional empirical analyses to check the robustness of our results in two different ways. Firstly, to test whether the results of this study are due to multicollinearity, the control variables have been deleted to determine whether the main effect and the moderating effect will change without the control variable. As shown in Table 5, the result is consistent with the result of the previous model.

Our second robustness check uses an alternative econometric method. We applied the OLS regression and probit regression as an alternative method. The results provided in Table 6 are consistent with the results shown in Table 4. Therefore, the various models demonstrate robustness to different model specifications.

Table 5: Robustness Check for Deleting Control Variables

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ln_Succeed_Expierience		0.14^{***} (0.02)	0.20^{***} (0.08)	0.95^{***} (0.09)	0.18^{**} (0.09)	0.22^{***} (0.09)
Ln_Succeed_Expierience ^2			-0.01^{***} (0.02)	-0.15^{***} (0.02)	-0.01^{*} (0.02)	-0.01^{*} (0.02)
Ln_Succeed_Expierience ×Diversity				-7.77^{***} (0.56)		
Ln_Succeed_Expierience ×Avg_Similarity					-1.02^{***} (0.23)	
Ln_Succeed_Expierience ×Ln_Complexity						0.01 (0.07)
Ln_Succeed_Expierience^2×Diversity				0.95^{***} (0.15)		
Ln_Succeed_Expierience^2×Avg_Similarity					0.38^{***} (0.06)	
Ln_Succeed_Expierience^2×Ln_Complexity						-0.03 (0.20)
Diversity	3.80^{***} (0.26)	3.69^{***} (0.27)	3.65^{***} (0.27)	1.11^{***} (0.31)	3.80^{***} (0.29)	3.69^{***} (0.28)
Avg_Similarity	-1.11^{***} (0.07)	-1.41^{***} (0.08)	-1.47^{***} (0.11)	-2.37^{***} (0.14)	-1.64^{***} (0.12)	-1.52^{***} (0.12)
Ln_Complexity	-0.14^{**} (0.04)	-0.16^{***} (0.04)	-0.17^{***} (0.04)	-0.07^{**} (0.04)	-0.16^{**} (0.04)	-0.18^{***} (0.04)
_cons	-2.73^{***} (0.14)	-2.67^{***} (0.15)	-2.66^{***} (0.15)	-2.88^{***} (0.16)	-2.60^{***} (0.19)	-2.63^{***} (0.15)
LR chi2	609.09	653.10	653.69	1168.70	739.11	667.99
Pseudo R^2	0.04	0.04	0.04	0.07	0.04	0.04
Obs#	48792	48792	48792	48792	48792	48792

Notes: Standard errors are included in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 6: Robustness Check for Alternative Econometric Method

	Probit				OLS			
Variable	Model 3	Model 4	Model 5	Model 6	Model 3	Model 4	Model 5	Model 6
Ln_Succeed_Expirience	0.61^{***} (0.04)	0.73^{***} (0.05)	0.60^{***} (0.05)	0.61^{***} (0.05)	0.05^{***} (0.00)	0.06^{***} (0.00)	0.05^{***} (0.00)	0.05^{***} (0.00)
Ln_Succeed_Expirience ^2	-0.07^{***} (0.01)	-0.10^{***} (0.01)	-0.07^{***} (0.01)	-0.07^{***} (0.01)	-0.01^{***} (0.00)	-0.01^{***} (0.00)	-0.01^{***} (0.00)	-0.01^{***} (0.00)
Ln_Succeed_Expirience ×Diversity		-3.11^{***} (0.28)				-0.49^{***} (0.36)		
Ln_Succeed_Expirience ×Avg_Similarity			-0.46^{***} (0.12)				-0.06^{***} (0.01)	
Ln_Succeed_Expirience ×Ln_Complexity				0.03 (0.03)				0.00 (0.00)
Ln_Succeed_Expirience^2× Diversity		0.45^{***} (0.07)				0.08^{***} (0.01)		
Ln_Succeed_Expirience^2× Avg_Similarity			0.16^{***} (0.03)				0.19^{***} (0.00)	
Ln_Succeed_Expirience^2× Ln_Complexity				-0.01 (0.01)				-0.00 (0.00)
Diversity	0.24^{*} (0.14)	0.32^{**} (0.15)	0.30^{**} (0.16)	0.25^{**} (0.14)	0.04^{***} (0.01)	0.02^{*} (0.01)	0.04^{***} (0.02)	0.04^{*} (0.01)
Avg_Similarity	-0.87^{***} (0.05)	-1.07^{***} (0.07)	-0.93^{***} (0.06)	-0.87^{***} (0.06)	-0.08^{***} (0.01)	-0.10^{***} (0.01)	-0.09^{***} (0.01)	-0.08^{***} (0.01)
Ln_Complexity	-0.07^{***} (0.02)	-0.04^{**} (0.02)	-0.07^{***} (0.02)	-0.07^{***} (0.02)	-0.01^{***} (0.00)	-0.01^{***} (0.00)	-0.01^{***} (0.00)	-0.01^{***} (0.00)
Ln_Participation	-0.26^{***} (0.01)	-0.22^{***} (0.01)	-0.26^{***} (0.01)	-0.25^{***} (0.01)	-0.03^{***} (0.00)	-0.02^{***} (0.00)	-0.03^{***} (0.00)	-0.03^{***} (0.00)
Ln_Prize	-0.12^{***} (0.02)	-0.12^{***} (0.02)	-0.13^{***} (0.02)	-0.13^{***} (0.02)	-0.01^{***} (0.00)	-0.01^{***} (0.00)	-0.01^{***} (0.00)	-0.01^{***} (0.00)
Ln_Views_Amount	0.13^{***} (0.03)	0.11^{***} (0.02)	0.13^{***} (0.03)	0.13^{***} (0.03)	0.02^{***} (0.00)	0.02^{***} (0.00)	0.02^{***} (0.00)	0.02^{***} (0.00)
Ln_Total_Submissions	-0.30^{***} (0.02)	-0.29^{***} (0.02)	-0.29^{***} (0.02)	-0.30^{***} (0.02)	-0.04^{***} (0.00)	-0.03^{***} (0.00)	-0.04^{***} (0.00)	-0.04^{***} (0.00)
Ln_Submit_Sequence	-0.12^{***} (0.01)	-0.12^{***} (0.01)	-0.12^{***} (0.01)	-0.12^{***} (0.01)	-0.01^{***} (0.00)	-0.01^{***} (0.00)	-0.01^{***} (0.00)	-0.01^{***} (0.00)
Ln_Submissions	0.29^{***} (0.02)	0.30^{***} (0.02)	0.29^{***} (0.02)	0.29^{***} (0.02)	0.03^{***} (0.00)	0.03^{***} (0.00)	0.03^{***} (0.00)	0.03^{***} (0.00)
_cons	0.67^{*} (0.17)	0.55^{***} (0.18)	0.73^{***} (0.19)	0.66^{***} (0.18)	0.31^{***} (0.02)	0.29^{***} (0.02)	0.32^{***} (0.02)	0.31^{*} (0.02)
LR chi2 / F-Statistics	1874.01	1599.57	1490.05	1485.50	87.84	81.86	76.04	74.60
Pseudo R^2 / R^2	0.11	0.13	0.11	0.11	0.05	0.06	0.05	0.05
Obs#	48792	48792	48792	48792	48792	48792	48792	48792

Notes: Standard errors are included in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

5. Conclusion and Discussion

This section will discuss our findings, followed by a discussion of the theoretical and managerial consequences of those findings.

5.1. Conclusion

This study was inspired by the theoretical debate surrounding the relationship between solvers' prior success experience and their chances of winning in crowdsourcing contests. On one hand, studies based on the perspective of the human capital theory hold that the past success experience has increased the accumulation and transformation of relevant knowledge and skills, thus increasing the chance of winning in a current crowdsourcing task [Archak 2010; Boudreau et al. 2011; Yang et al. 2009; Mo et al. 2018]. On the other hand, research that draws on the cognitive psychology and creativity perspective highlights the disadvantages of past success experience, such as cognitive fixation, competency traps, and core rigidities [Huckman et al. 2009; Bayus 2013]. Our study states that neither conceptualization can fully capture the complex nature of this relationship in isolation. By integrating the two seemingly opposing theoretical streams, we develop a framework that considers the pros and cons of historical experience and argues that the relationship between solvers' prior success experience and their chances of winning in current crowdsourcing tasks follows a U-shaped pattern.

Specifically, the reconciliation of human capital and cognitive psychology theories allows us to reveal the penetration between the two contradictory theoretical views. Namely, we demonstrate that the explanatory power of the two opposing theoretical perspectives depends on the respective levels of past success experience that a solver has acquired. For instance, the human capital theory may be more informative for solvers who have moved from low to moderate levels on the continuum of past successful experience and who are likely to realize a higher probability of winning in the current crowdsourcing contest. At the same time, from moderate to extensive levels of past success experience, the human capital perspective seems to increasingly lose explanatory power because too many experiences no longer provide new knowledge and skills that transfer to future tasks. Instead, the cognitive psychology theory gains more explanatory power from moderate to extensive levels of past success experience as solvers with too much historical experience may face cognitive fixations that reduce solution innovation, which is the key to winning crowdsourcing contests.

Our findings also reveal that the observed U-shaped relationship is significantly influenced by experience diversity and the similarity between experience and the current task. As illustrated in Figure 2-a, solvers whose past success experience comes from more diverse categories of tasks are slower to accumulate knowledge and skills transferred to future tasks in any category, resulting in the slow upward trend in the first half of the curve. Meanwhile, for moderate to extensive levels of past success experience, the more diverse the experience is, the less its negative impact is coming from cognitive fixation, which is shown in the slow downward trend in the latter part of the curve. Different from diversity of experience, the similarity between experience and the current task reflects the matching degree of experience and tasks. As shown in Figure 2-b, experience more similar to the current task can lead to a higher chance of winning at the initial point. However, with the continuous growth of relevant experience, the new knowledge and skills brought by additional similar experience are relatively less, and the marginal utility of the increase in related experience becomes relatively lower; that is, the upward trend of the first half of the curve is slower. Meanwhile, when the current task is more similar to one's past success experience, the experience more easily transferred to the solution of the current task, which weakens the negative effects brought by cognitive fixation. Thus, the downward trend in the latter part of the curve appears later and has a smaller slope.

5.2. Implications

Our findings contribute to the literature in a number of ways, including identifying promising new research directions and creating intriguing practical implications, which we will explore in greater depth in the following section.

5.2.1. Theoretical Implications

This study makes several significant contributions to the literature from the following perspectives. On one hand, we offer a step toward the reconciliation of the two contradictory theoretical streams on the relationship between solvers' prior success experience and their chances of winning in crowdsourcing contests, as follows: (a) the one that draws on human capital theory to highlight the "bright side" of historical experience [Borman et al. 1993; Sturman 2003] and (b) the one that subscribes to the cognitive psychology theory to underscore the "dark side" of experience related to future performance [Jansson & Smith 1991; Leonard-Barton 1992]. Drawing on the TMGT framework, our theory and empirical support for the U-shaped relationship complement recent findings showing that historical experience must be considered as a double-edged sword that can be related to both beneficial as well as detrimental effects [Kc & Staats 2011; Sivatte et al. 2019; Mueller et al. 2020]. Our findings show that future performance in crowdsourcing contests, especially in innovation tasks, increases with the solver's past successful experience up to a certain level. However, too much success experience can negatively affect the chance of winning by forming cognitive fixation. Therefore, our study brings together two contrasting views in the prior research and provides a novel understanding of the complicated, non-linear relationship between past success experience and future performance.

However, due to the constraints of data availability, previous studies have used only numerical data to measure past success experience and have neglected the text data, the latter of which can bring more valuable results via text analysis. To fill this critical research gap, our study used text mining technology to analyze text data collected from Epek.com and then constructed three moderating variables (the diversity of solvers' past experience, similarity between prior success experience and the current task, and task complexity) to explore the moderating effects of the characteristic factors of tasks and experience on the main effect. Our study is among the very few that have made headway in this direction. The results confirm these moderating effects from the diversity of solvers' past experience and the similarity between prior success experience and the current task. The current study thus sheds new light on crowdsourcing experience and performance by capturing the characteristic factors of tasks and experience through text mining.

5.2.2. Managerial Implications

This study also yields several direct practical implications. First, the results guide solvers in effectively using their historical success experience to improve their odds of winning in future crowdsourcing tasks. Solvers should make full use of the advantages brought by successful experience and try their best to choose tasks similar to their past experience so as to better transfer the knowledge and skills accumulated in prior crowdsourcing contests to the new tasks and win again. Furthermore, in the long term, to avoid, as far as possible, the negative impact of cognitive fixation on innovation performance, solvers should increase the types of tasks they participate in, thus making their historical experience more diversified and finally achieving sustainable development in crowdsourcing contests.

Second, our findings also provide helpful insights for seekers in crowdsourcing contests. A solver's past success experience is one of the essential evaluation indicators for the seeker to choose the best solution. According to the results of this study, seekers should not merely focus on the quantity of the solver's past success experience but should also pay attention to the diversity therein and its fit with the current crowdsourcing task so as to form a more comprehensive and reliable evaluation.

Third, the empirical results provide a reference for crowdsourcing platform managers to develop a more efficient task and solver recommendation mechanism. In this study, we analyze the impact of different characteristics of historical experience and tasks on the non-liner relationship between past success experience and future crowdsourcing performance. The conclusion provides guidelines for a crowdsourcing platform to recommend suitable potential solvers to the seeker and to recommend suitable tasks to the solvers in their crowdsourcing platform based on the solvers' historical data of success experience so as to improve the operation efficiency of a crowdsourcing platform.

6. Limitations and Future Directions

As with any study, this research inevitably has several limitations. First, we test our research model only in the context of the Chinese crowdsourcing platform, and almost all seekers and solvers in this platform are Chinese. To make the proposal more generalizable and increase its external validity, future research can verify our research model in different countries and compare the effects from different cultural values. Second, this study employs a comprehensive crowdsourcing platform as the research data, which has many types of crowdsourcing tasks. And in this study, all types of tasks are taken as a whole to test the generality of our research model. Investigating how different types of crowdsourcing tasks influence the relationship between past success experience and future performance in different ways may be an exciting direction for future research. Third, the research model can be applied in future studies aiming to develop a more efficient task and solver recommendation mechanism.

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