Competition matters! Self-efficacy, effort, and performance in crowdsourcing teams

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Abstract:

Advances in information technologies (IT) have enabled organizations to seek solutions for their business problems from beyond their own workforce through digital crowdsourcing platforms. In the most common form of crowdsourcing, teams that offer solutions compete for rewards. Thus, a question of interest is whether competition is a key crowdsourcing characteristic that influences how teams allocate their effort and achieve desired performance. Motivated by this question, we investigate how competition moderates the relationship between self-efficacy and effort using comprehensive, time-variant data collected from crowdsourcing teams that completed a project under competitive and non-competitive conditions. Under competitive conditions, self-efficacy shows a positive effect on effort, which in turn, affects performance positively. Whereas, under noncompetitive conditions, self-efficacy has a negative effect on effort and subsequently on performance. Our results also show a recursive relationship between self-efficacy and performance, in which performance subsequently affects self-efficacy positively. Thus, inducing a sense of competition through competitive reward structures and IT-based "gaming elements" helps improve team effort and subsequent performance. We also tested for mediation of team motivation in the self-efficacy and effort relationship, and we found that motivation partially mediates the relationship. Based on our findings, implications for both theory and practice are discussed.

Keywords: Crowdsourcing | Competition | Self-efficacy theory | Control theory | Social comparison | Gamification

Article:

1. Introduction

Rapid advances in information technologies (IT) have disrupted and provided new opportunities for organizational problem-solving strategies. IT-enabled crowdsourcing platforms have become a popular method to solve organizational problems by accessing global knowledge and expertise. Crowdsourcing platforms publicly invite a large number of people to perform a task that is typically performed by an employee or a contractor [1]. Such platforms are being successfully used in various areas, such as predictive analytics (Kaggle.com), international business (X-Culture.org), software development (TopCoder.com), R&D (InnoCentive.com), healthcare (CrowdMed.com), and graphic and art designs (Threadless.com) [2,3]. Organizations are increasingly using these cost-effective [4] and low-risk [5] crowdsourcing platforms [2,6] to form global outsourcing teams of problem solvers that find innovative solutions to organizational problems [7]. Key reasons for using crowdsourcing teams include getting access to highly specialized problem-solving skill sets and increased brand visibility [8]. Prior studies have reported that 85% of the best global brands have used crowdsourcing teams to solve business problems [9]. With their growing popularity, crowdsourcing has emerged as a mainstream research area in the information systems (IS) discipline, and improving crowdsourcing team performance has become an important area for academic research (see [2], [10], [11], [12], [13]).

Previous research on crowdsourcing teams has observed that task-design characteristics such as reward structure [14], project duration, and project complexity [15] can impact team performance. Crowdsourcing teams are different from traditional organizational teams, as they are not only geographically distributed but also typically compete against each other for rewards. These rewards can be both tangible, such as monetary, or intangible, such as online reputation. These unique characteristics motivated us to examine the role of competition as a key task-design characteristic in crowdsourcing teams. Building on existing literature, we identified two task-design settings (competitive and non-competitive) [16], [17], [18] and examined how these two settings would predict crowdsourcing effort and subsequent performance. We used the tenets of social comparison theory to design the competitive condition. Social comparison theory proposes that people tend to evaluate themselves by comparing themselves to others on various facets [6,19]. As per the theory, "social comparison on a mutually relevant dimension (e.g., profit) with a commensurate counterpart (e.g., rival) generates competition" ([20] p.971).

In addition to task-design characteristics, characteristics of problem solvers in crowdsourcing teams can also predict performance. Recently, a few studies have observed that solvers' skill [14] and effort [21] can improve the quality of solutions developed by the team. But, little else is known about how other key solver characteristics affect crowdsourcing performance.

Self-efficacy is a defining solver characteristic as it represents one's own belief in the ability to perform a behavior [22]. In the context of crowdsourcing teams, team self-efficacy would represent a team member's belief and confidence in the team's ability to successfully complete the task. The present study explores self-efficacy's influence on effort and subsequent performance among crowdsourcing teams in both competitive and non-competitive situations. Self-efficacy of crowdsourcing teams is an interesting and relevant characteristic to examine for various reasons. First, the psychology and team literatures clearly reveal self-efficacy as a key characteristic that could predict effort and performance [23], [24], [25], [26]. Second, socio-cognitive and control theorists have debated the relationship between self-efficacy and performance for decades. Socio-cognitive theorists support the self-efficacy theory, proposing that self-efficacy strongly increases performance by increasing motivation and escalating the level of effort [27,28]. Control theorists, on the other hand, challenge this view by proposing that the impact of self-efficacy on performance could be positive, negative, or null, depending on how self-efficacy beliefs are held by individuals [28,29]. For example, negative or null effects of high self-efficacy could ensue when solvers become optimistic about their nearness to the problem-solving goal, and exert less effort toward goal achievement [29].

There is also an ambiguity regarding the direction of causality, i.e., whether self-efficacy is a driver of crowdsourcing team performance or is it a result of past team performance [30]. According to control theorists, the positive relationship observed between the two could be due to the effect of past team performance on self-efficacy, and not vice-versa [30,31]. This perspective challenges the classical notion that self-efficacy predicts performance and makes self-efficacy furthermore important to examine in crowdsourcing teams. Previous literature on crowdsourcing is conspicuously silent on this issue.

Given our focus on the role of competition, we examine the moderating role of competition on the relationship between self-efficacy and effort. We also realize that self-efficacy may not act alone and an important mediating variable may be motivation. Bénabou and Tirole [32] argue that "self-confidence is valuable because it improves the individual's motivation to undertake projects and persevere in the pursuit of his goals, in spite of the setbacks and temptations that periodically test his willpower" ([32] p. 877). Therefore, higher self-efficacy could increase solvers' motivation to act [28,32], which, in turn, could lead to higher effort. Finally, we examine the effect of effort on performance. In this pursuit, we collected comprehensive time-variant data from 266 teams using X-Culture [3], a leading online crowdsourcing platform for academia, and relied on the theoretical underpinnings of social comparison, self-efficacy, and control theories to examine the following research questions:

> 1) How does competition impact the nature of the relationship between self-efficacy and effort in crowdsourcing teams?
>
> 2) Does motivation mediate the relationship between self-efficacy and effort?
>
> 3) Does self-efficacy predict effort and subsequent performance?
>
> 4) Do self-efficacy and performance share a recursive relationship?

In the last question, the issue to examine is whether solvers' self-efficacy acts as *both* a predictor of future performance as well as an outcome of their past performance?

Our study makes three significant theoretical contributions and parallel practical contributions. First, the study shows that intensifying competition through rewarding the top-rankers, and using gaming elements to provide them with interim feedback about their comparative performance, improves crowdsourcing performance. In doing so, this study extends the application of social comparison and self-efficacy theories to IT-enabled crowdsourcing platforms. Interestingly, it also confirms the claim of the gamification field that "gaming elements" can enhance participants' motivation and engagement in crowdsourcing environments [33].

Second, our findings show that dynamic and competitive crowdsourcing settings can contribute to the long-standing debate between socio-cognitive theorists and control theorists [28] and reconcile some of their conflicting findings. Specifically, the study shows that (i) solver self-efficacy has a positive effect on effort and subsequent performance in a competitive crowdsourcing setting, which supports the self-efficacy theory; and (ii) self-efficacy has a negative effect on effort in a noncompetitive setting, which supports the control theory. In practice, these findings can be used to induce appropriate levels of competition in crowdsourcing teams to improve effort and subsequent performance.

Finally, our study contributes to the ongoing debate regarding the direction of causality between self-efficacy and performance, i.e., whether self-efficacy is a driver of performance or a product of past performance. Our results suggest that self-efficacy and crowdsourcing performance share a recursive relationship, and gaming technologies can help exploit these recursive effects to improve overall performance. Again, these findings can be put to practical use to improve effort and performance.

The remainder of this paper is organized as follows. The next section provides the theoretical foundation for the study. It is followed by an articulation of our research model and the hypotheses that follow from it. Subsequently, we describe the data collection procedures and measures, and then present our findings. The paper concludes with a discussion of theoretical and managerial implications, followed by directions for future research.

2. Theoretical background and related literature

Competition is a key factor in the crowdsourcing context, yet its effect has been rarely investigated with a few exceptions (e.g., [2]). Although the effect of self-efficacy on performance is a widely investigated topic in the psychology literature, self-efficacy studies in the IS field are limited to general computer self-efficacy (i.e., "judgment about one's capability to use computers" [34] p.192) [22]. In this study, to understand the role of competition, we complement the literature by investigating the effect of self-efficacy on team effort and subsequent performance in a crowdsourcing setting. Self-efficacy, control, and social comparison theories provide the theoretical foundation for this study.

2.1. Crowdsourcing context

Crowdsourcing is a problem-solving model that uses digital platforms to seek knowledge from geographically distributed individuals to solve pressing business problems in various disciplines (e.g., software development, healthcare, and consulting). It can improve the efficiency and effectiveness of problem-solving processes [35]. Typically, crowdsourcing involves three stakeholders – clients (*seekers)* looking for solutions to business problems, motivated individuals (*solvers*) who participate in teams to solve an organization's problems, and *platform providers* who facilitate the interaction between the seekers and solvers [2,8]. In its most common form, crowdsourcing takes a competitive nature where teams or individual solvers compete with each other for a reward [2]. For example, a Netflix competition involved a $1 million reward to develop a recommendation algorithm.

Prior literature in crowdsourcing has focused on how task-design and platform characteristics such as reward structure [14,36], task duration [15], task complexity [15], and perceived ease of use of platform [10] influence crowdsourcing outcomes such as the number of solvers participating in a project, solver's project completion rate, number of solutions, and the quality of solutions. Some recent studies have also investigated how solvers' or solving teams' characteristics such as skill or experience [37], effort [6], and team structure [2] affect crowdsourcing performance outcomes.

A few studies have investigated the impact of interim performance feedback (e.g., direct performance feedback or relative performance feedback) on crowdsourcing outcomes such as effort and performance [6,38]. Dissanayake et al. [6] showed that relative performance feedback through open leaderboards intensifies the competition, and solvers tend to allocate more effort when they get closer to the winning positions, which, in turn, improves performance. Yang et al. [15] also reported that feedback can have a motivating impact on solvers, but the authors did not empirically validate their claim. Wooten and Ulrich [38] used experimental data from a logo design contest to show that feedback leads to less variations in solutions because solvers tend to tailor their solutions to meet the seeker's preference. In another study, Lee et al. [11] used leaderboard feedback to show that systematic bias can impact performance. Morschheuser et al. [39] conducted a literature review of gamified crowdsourcing studies and identified that competition-based designs with leaderboards have, very often, been used to motivate individuals in many crowdsourcing environments.

The competitive nature of crowdsourcing makes crowdsourcing teams different from other co-located and distributed teams that have been investigated in prior literature. Competition may lead to solvers putting in more effort. In this new context, prior findings from the literature may not hold or may not be completely valid. For instance, it has been shown that the general belief that "the centrality of experts enhances team performance" may not hold true in competitive crowdsourcing environments [2].

2.2. Self-efficacy, motivation, effort, and performance

Self-efficacy is defined as "people's belief regarding their capability to succeed and attain a given level of performance" ([30] p.531). Self-efficacy and control theories provide two opposing views of how self-efficacy impacts level of effort and subsequent performance. As per self-efficacy theory [27], individuals' self-efficacy enhances their performance in three ways: it increases the difficulty of self-set goals, enhances the level of effort put forth, and strengthens persistency [30]. Self-efficacy leads to continuous improvement through positive discrepancy-creation by setting goals that are higher than one's level of past performance [26,40]. It determines how much effort people allocate, and how long they continue to put in effort. Typically, low self-efficacy can result in reduced effort or completely giving up the task, whereas high self-efficacy can result in greater effort to master the challenge [41]. This tendency also serves as a "motivational inducement for enhancing effort" ([42]p.1017). Bandura [41] mentioned that "In applying existing skills, strong self-efficaciousness intensifies and sustains the effort needed for optimal performance" ([27] p.123). By affecting the effort invested in a given task, self-efficacy can also determine the level of performance achieved [41].

According to the self-efficacy perspective, self-efficacy typically shows a positive relationship with effort and subsequent performance. Prior research in various disciplines also supports this relationship. Seo and Ilies [28] showed in an internet-based stock investment simulation study that self-efficacy is positively related to effort and subsequent performance. Multiple studies in sport disciplines have also shown that players self-efficacy positively influences their performance [43]. In fact, a number of meta-analytic studies have also reported an overwhelming evidence of a positive relationship between the two [28,30,44,45]. For instance, Stajkovic and Luthan [45] conducted a meta-analysis based on 114 studies and found a strong positive correlation between self-efficacy and performance. They also observed that this correlation transformed to a "28% increase in performance due to self-efficacy" ([45] p. 252).

Self-efficacy theory also suggests that self-efficacy has a positive relationship with motivation [26]. Bandura ([46] p.392) mentioned that "the types of outcomes people anticipate depend largely on their judgments of how well they will be able to perform in given situations" [47]. Motivation is driven by outcome expectation, and prior crowdsourcing studies have reported that the motivation to put in effort typically increases when solvers become confident of achieving their outcomes [6].

In contrast, control theory [29] scholars have argued that self-efficacy can have a null or negative effect on effort and subsequent performance [26]. Control theory takes a negative discrepancy-creation (discrepancy-reduction) view, where individuals compare their performance to a reference point, or a standard, and as they move closer to this standard, they reduce their effort [26,30,40]. One possible explanation for this behavior is "when individuals believe that they are meeting their goals, they are less likely to allocate resources (i.e., time and effort) towards those goals when compared with when they believe that they are not meeting their goals" ([26] p. 607). Multiple empirical studies have supported this view. Vancouver and Kendall [48] observed that self-efficacy negatively affected motivation and performance in a learning context. In a different context of complex tasks, Cervone and Wood [49] provided evidence of a negative correlation between self-efficacy and performance. They identified the reason as individuals becoming overconfident of their abilities [26]. In other words, individuals formed judgments about their abilities that exceeded their true ability [50]. Literature has shown strong evidence of this observation [49,50]. In an experiment conducted with 106 students, Moores and Chang [51] showed that overconfidence negatively impacted the relationship between self-efficacy and subsequent performance.

To add to the debate between self-efficacy and control theorists, prior findings are also conflicted about the *directionality* of the self-efficacy and performance relationship [28,52]. For example, Sitzmann and Yeo [30] concluded that self-efficacy is more a product of past-performance than a driver of future performance.

The definitive importance of self-efficacy as a key solver characteristic, and yet the overall inconclusive nature of the relationship between self-efficacy, motivation, effort, and subsequent performance, led us to examine this relationship in the crowdsourcing setting. Specifically, we wanted to explore both the nature and directionality of solver self-efficacy, effort, and performance relationship, as well as the role of solver motivation. Theoretical underpinnings to explore these inconclusive findings were derived from the tenets of social comparison theory.

2.3. Social-comparison, performance feedback, and competition

Social comparison is defined as “the tendency to self-evaluate by comparing ourselves to others” ([19] p.634). As per the social comparison theory, people desire to perform well (“unidirectional drive upward”) by reducing the gap between themselves and others (“targets”) [19]. Several factors contribute to these comparisons. These include incentive structures (e.g., rewarding the winner), proximity to standards (i.e., distance to the winning position), and the number of competitors [6,19]. Garcia et al. [20] observed that competition among commensurate rivals is intensified in the proximity of a meaningful standard [20], such as a monetary reward. Additionally, in competitive auction settings, relative performance-feedback using gaming elements such as open leaderboards is known to facilitate social comparisons among participants, resulting in competitive arousal [53].

Dissanayake et al. [6] applied the social comparison theory to investigate solvers’ behaviors in the presence of open leaderboard and rewards for top performing teams. They found that rewarding the winners (i.e., setting a meaningful standard at the top) results in intense competition due to social comparisons among solving teams as they get closer to winning positions, and that, in turn, enhances their effort and subsequent performance. They also argued that motivation to put forth effort will increase when solvers become confident that they have a higher chance of winning [6].

Eriksson et al. [54] investigated the effect of relative performance feedback combined with incentive schemes on employees’ effort, and found evidence for positive peer-effect in winner-takes-all tournaments. On the other hand, it was also observed that relative performance-feedback may not have a positive impact on effort under noncompetitive competitions. For example, in an experimental study, Barankay [55] observed that in the absence of meaningful standards, relative performance-feedback showed a negative impact on employees’ effort.

In summary, using the tenets of social comparison theory, it seems reasonable to argue that the nature and direction of self-efficacy, effort, performance relationship in crowdsourcing teams may be moderated by the *competition* context. Thus, in crowdsourcing competitions, characterized by a meaningful reward and relative performance feedback, self-efficacy may further improve effort and thus performance. When crowdsourcing teams that are competing for a meaningful reward are given relative performance-feedback (e.g., showing their relative ranks on a leaderboard), they would set themselves a new goal that is slightly higher than their previous performance. The presence of a meaningful reward and relative performance feedback would facilitate social comparison, further intensifying competition among teams and moving them toward the winning position. Thus, in crowdsourcing competitions, not only would the positive effects of self-efficacy on performance dominate but would also be recursive in nature. Based on this theoretical premise, we now articulate our research model and formulate the resulting hypotheses.

3. Research model and hypotheses

We take the building block approach and present our research model in two stages. Doing so provides greater conceptual clarity and also helps us tease out and better examine the proposed relationships. In the first model, we explore the impact of self-efficacy on solver effort, and how competition moderates this relationship. We also propose and examine if motivation mediates the relationship between self-efficacy and effort. In the second model, we propose and test the overall relationship between solver self-efficacy, effort, and subsequent performance by examining the entire chain of effects.

3.1. Impact on solvers' effort

One's performance is a function of one's skill and the level of effort one exerts [6,56]. In another crowdsourcing setting, Dissanayake et al. [6] indicated that "enhancing either the skills or the efforts of participants increases the chances of winning through improved quality of the solution" (p. 403). One's skill does not change much within a short duration, such as in a project environment. However, the level of effort may not be fixed through the duration of a project; therefore, we focus on effort in our study. Understanding what factors impact the level of effort would help improve crowdsourcing performance by improving team members' effort. As per self-efficacy theory, one's self-efficacy has been identified as a key determinant of one's effort allocation [28,41].

Self-efficacy theory differentiates between efficacy expectation and outcome expectation. Outcome expectation is defined as "the person's estimate that a given behavior will lead to certain outcome," while efficacy expectation is defined as "the conviction that one can successfully execute the behavior required to produce the outcomes" ([27] p. 193). The theory argues that although solvers believe that a set of activities lead to a particular outcome, they can have serious doubts about whether they can successfully perform those activities [27]. Thus, the self-efficacy theory views the efficacy expectation as a mechanism of operation [27]. Efficacy expectations would have a major effect on solvers' choices of what to do, how much effort they would put forth, and how long they would continue to expend efforts [42]. In general, self-efficacy would result in increased solver effort [27], i.e., when solvers believe that their team can successfully complete the task, they are likely to exert more effort to meet their goal, compared to the solvers who do not believe in their team's ability to meet the goal [26]. Hence, we have the following hypothesis:

Hypothesis 1 (H1). *Solvers' self-efficacy positively influences their effort.*

Although self-efficacy theory has generally identified a positive relationship between self-efficacy and effort, empirical evidence has shown that the relationship can also be negative or null [30]. We argue that the direction of the relationship would depend on the design of the task setting, particularly the presence of competition. Competitiveness or desire to perform better than others is created through social comparisons, which are facilitated by the relative performance-feedback given to the teams [6].

As per the social comparison theory, competitiveness intensifies when solvers get closer to the standard (e.g., winning position or top ranks). A monetary reward typically establishes a mutually relevant dimension for the teams and sets the top rank as a meaningful standard [22]. Thus, when solvers get closer to the ultimate goal, they tend to exert more effort. Previous studies have shown that solvers strategically allocate effort based on interim feedback from open leaderboards [6]. Moreover, every time when relative feedback is provided using a leaderboard, the proximity of solvers to the meaningful standard and commensurate rivals can change.

However, the mutually relevant dimension would not change [6]. As per the social comparison theory [57], contestants in such an environment "are likely to have a "drive upward" to perform well, as they continually evaluate themselves vis-à-vis those who are placed higher on the leaderboard" ([6] p.400).

Furthermore, efforts are costly. Getting closer to the top rankings increases the probability of winning. Thus, when solvers get closer to winning targets, they would become more confident that they can win the competition. This would motivate them to expend more effort [58]. Thus, we argue that interim ranking feedback through an open leaderboard would increase their self-efficacy, which, in turn, would increase their effort as they move toward the target.

On the other hand, in a non-competitive setting, where there is no reward for winners and no way of comparing their performance with others', the teams' motivation would be to perform at a satisfactory level, based on their self-set goals, but not necessarily become the best performing team. There is no strong "upward driver" or desire to achieve higher rankings than others. Thus, in such an environment, it is plausible that they would work in a "discrepancy-reduction" manner as suggested by the control theory. That is, when they believe they performed well (i.e., high self-efficacy), they would expend less effort toward their goal attainment than when they believe that they did not perform well [30]. Hence, we propose the following hypothesis:

> **Hypothesis 2 (H2).** *Competition moderates the relationship between solvers' self-efficacy and effort, such that the positive influence of self-efficacy on effort is stronger in a competitive setting than in a non-competitive setting.*

As per self-efficacy theory, motivation is "primarily concerned with activation and persistence of behavior" ([27] p. 193). There are two forms of motivation. First, motivation could be inspired by the expectations of future rewards (i.e., predicted outcomes) [42]. This extrinsic motivation, such as the desire to win a reward or successfully complete the project, can induce greater effort. These outcome expectations depend on one's beliefs about how well to perform in a given situation [47]. Thus, when team members become confident that they can perform well that, in turn, motivates them to exert more effort. Second, motivation also derives from goal-setting and self-evaluative reactions [27]. That is, an individual sets a goal and persists in the behavior until the self-set goal has been reached. The difference between the goal and current performance acts as a motivational inducement to exert effort [42].

Bénabou and Tirole [32] state that "Self-confidence is valuable because it improves the individual's motivation to undertake projects and persevere in the pursuit of his goals, in spite of the setbacks and temptations that periodically test his willpower" ([32] p. 877). Therefore, higher self-efficacy would increase solvers' motivation to act [28,32]. Thus, we argue that higher self-efficacy leads to motivation, which, in turn leads to higher effort. Hence, we have the following hypotheses:

> **Hypothesis 3 (H3).** *Solvers' self-efficacy positively influences their motivation.*

> **Hypothesis 4 (H4).** *Solvers' motivation is positively related to their effort.*

Fig. 1 summarizes the first part of the research model.

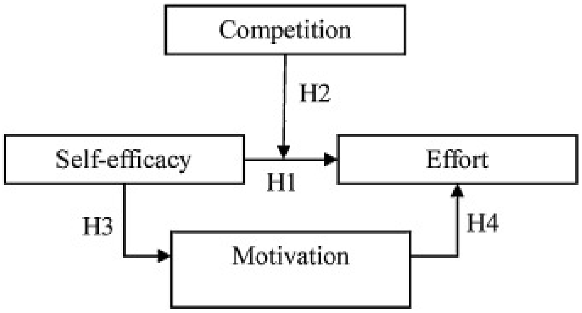

Fig. 1. Research Model Part I: Self-Efficacy and Effort.

3.2. Impact on solvers' performance

According to self-efficacy theory, self-efficacy enhances performance and motivation by increasing effort [28]. Solvers efficacy expectations and outcome expectations help solvers to determine the way in which they should allocate resources to reach a desired level of outcome (performance) [27]. Resources refer to the extent and the length of effort [26]. Thus, solvers set performance targets based on their expectations and continue to expend effort until those targets are met. The theory also says that performance is influenced by the cumulative effects of one's efforts [27].

In crowdsourcing context, studies have shown that solvers' effort contributes to their performance [6,54]. Higher effort leads to higher quality solutions. Hence, we have the following hypothesis:

Hypothesis 5 (H5). *Solvers' effort is positively related to performance.*

Both control theorists and socio-cognitive theorists agree that past-performance has a causal effect on self-efficacy [30,59]. Self-efficacy theorists believe that performance accomplishments are one of the main sources of efficacy expectations [27], which are typically developed through repeated success [27]. As individuals experience repeated success, they establish higher goals to achieve [28]. Control theorists also propose that the reason for performance differences between people with different levels of self-efficacy is that people with higher self-efficacy have been more successful in the past [30]. In fact, Vancouver [26] even argued that the classical positive effect of self-efficacy on performance could be a result of performance influencing self-efficacy rather than self-efficacy influencing performance. In the crowdsourcing context, performance feedback relative to other teams would make solvers aware of the level they are trying to achieve [30,60,61], and improve their confidence and self-efficacy beliefs, as they work toward their goals.

In non-competitive crowdsourcing tasks, given the absence of a clearly set goal and relative performance feedback, the dynamics underlying the causal effect of performance on self-efficacy may be different, but the effect still persists. Under such conditions, perceptions of their interim performance may enable solvers to learn, and the cumulative effect of learning from past performances may strengthen solvers' beliefs of future success [28,30]. In other words, interim performance is expected to have a strong positive effect on solver's self-efficacy beliefs. Hence, we have the following hypothesis:

> **Hypothesis 6 (H6).** *Solvers' interim performance is positively related to their self-efficacy.*

Fig. 2 summarizes the complete research model. The dotted lines indicate the effect of interim performance (lagged performance). In the competitive setting, interim relative performance feedback was provided to teams through a leaderboard. No such performance feedback was provided in the non-competitive setting.

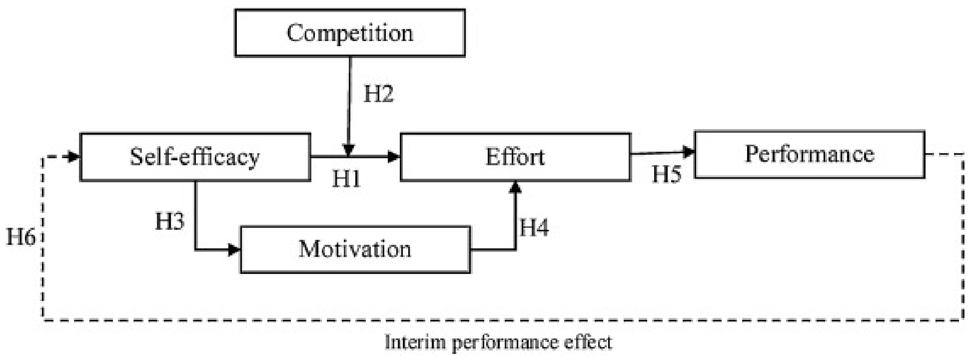

Fig. 2. The Full Research Model.

4. Method

4.1. Research setting and data collection

The data for this study came from the X-Culture platform,[1] a specialized crowdsourcing platform for academia that focuses primarily on promoting applied international business (IB) learning [3]. Each semester, the X-Culture platform holds an international business competition that attracts approximately 5000 business students from more than 130 universities in 40 countries on six continents. These students work in teams of four to nine members; usually each team member is from a different country. In every round of the competition, about a dozen corporate clients present their real-life business challenges. The students essentially serve as solvers and develop solutions for the IB challenges presented by their corporate clients. Including pre-project activities and post-project presentations, the X-Culture project takes up an entire semester.

The X-Culture platform has similarities and some differences when compared to a traditional crowdsourcing platform. Similar to any other crowdsourcing platform, three parties are involved: seekers, solvers, and a platform provider. Companies (seekers) present their business challenges, and thousands of students (solvers) from various geographical locations and cultural backgrounds team up and work on solving those challenges, and the platform provider is X-Culture. Unlike other crowdsourcing platforms, X-Culture actively promotes and encourages instructors and students from different geographical locations to participate in these challenges.

[1] http://www.x-culture.org/.

X-Culture has worked with many companies all over the world, including Mercedes-Benz, Home Depot, Louis Vuitton, and Plastic Revolutions (X-Culture.org).

According to X-Culture, student performance is closely monitored throughout the project. The final output – the team reports, are independently evaluated on a multidimensional scale by five to seven international business experts. Each semester, the expert panel is comprises about 140 professors whose students participate in the project. By and large, each team's report is evaluated by a different set of appraisers. Specifically, each professor is responsible to evaluate the reports from the team that his/her students are members of, and typically evaluates 20–50 reports. As the students are assigned to teams on a random basis and each team comprises a combination of students representing a random collection of countries and universities, the assignment of appraisers to teams can be considered random. The fact that each professor is evaluating reports from the teams where one of his or her students is a member means that all appraisers are motivated, when it comes to both the effort they put in the work and any favoritism they display (if any at all). If there is any bias, it would vary randomly across the appraisers. Thus, the threat of a systemic bias is minimal, and there is no reason to believe that the relative ratings of the reports are affected. The resulting evaluations provide a reasonably reliable and valid estimate of the quality of the project participants' work.

The X-Culture data used in this study are from the 2016 and 2017 rounds of the crowdsourcing competitions. The 2016 round included a non-competitive setting, while the 2017 round included a competitive setting. The total sample comprised 1449 students from 49 universities in 19 countries around the world. Overall, the sample size was 266 teams, with 108 teams in the competitive setting, and 158 teams in the non-competitive setting. Weekly deliverables for interim performance evaluations were collected for four different time periods: after the initial brainstorming stage, after the initial decision and choice stage, after the extended draft stage, and after the rough draft stage. Of all participants, 50.2 percent were female, and the average age of solvers was 23.3 years. In terms of educational level, 31.8 percent were graduate students (mainly MBA) or equivalent, while the rest were undergraduate students or equivalent. Solvers had an average of 8.5 months of prior international experience (travel, study abroad, or work overseas). Many solvers were expatriates and nearly 17 percent grew-up in a different country than their current location.

We collected data from teams that participated in two similar crowdsourcing projects addressing a real business challenge. The competitive setting included several factors that social comparison theory suggests would induce competition, namely a mutually relevant dimension, a meaningful standard, and commensurate rivals [6]. In the competitive setting, three winning teams were selected at the end of the project and each member of the winning teams was awarded a $500 travel stipend. This monetary reward not only acted as a relevant factor for everyone but also set a meaningful standard (i.e., to achieve top rankings). The quality of the weekly deliverables was evaluated and ranked weekly by appraisers, and the relative performance (i.e., the team rank) was displayed on a public leaderboard. The weekly deliverables were distributed to the appraisers on a random basis so that each report was independently evaluated by three or four appraisers. The evaluations for each submission were averaged across the raters, and the overall averages were used to rank the weekly submissions. The leaderboard reported only team rankings but not the ratings of their work. In doing so, it also worked as a tool for positive discrepancy-creation. This further encouraged upward comparisons as teams continuously set new goals (i.e., target rank) based on their past performance (i.e., current rank) to compete with other teams that were slightly better than them. In the noncompetitive setting, leaderboard and monetary rewards were absent, but all other mechanisms were the same as for the competitive setting.

Both projects had an active phase (almost daily interaction among the project participants) that lasted for 8 weeks. Additionally, the project participants typically had about four weeks of pre-project preparation and many spent a few more weeks after the project presenting their work and reflecting on their experiences. Weekly surveys were used to collect additional information related to team members' motivation, self-efficacy, effort, clarity, and team enjoyment. The operationalization of each variable is explained below.

4.2. Main variables

All variables except performance (i.e., quality of the solutions presented by the teams) were measured at the individual level. As appropriate, averages of individual level scores were used in the analyses to raise constructs to team level [62].

4.2.1. Performance

We used relative performance (ranking) as a measure of team performance. The platform ranks teams based on their interim performance at the end of each week. Thus, lower rank meant better performance, and vice-versa (e.g., rank #1 means best performance).

4.2.2. Motivation

Team motivation was calculated by taking the average of team members' self-reported level of motivation. The team members' motivation was measured weekly by asking them to report how motivated they felt to continue working hard on the project. They could choose values between 0 (I am NOT motivated at all) to 100 (I am VERY motivated).

4.2.3. Self-efficacy

As per the literature, evaluating team self-efficacy is a two-step process: First, team members shift the reference from the individual to the team level. Second, the individual beliefs are aggregated to the team level [63]. Thus, team members' self-efficacy was measured weekly by asking team members to report how confident they felt about their team's ability to successfully complete the project. They could choose values between 0 (I don't think my team will be able to complete the project) and 100 (I am confident my team can complete the project and produce a high-quality solution). Then, team self-efficacy was calculated by taking the average of team members' self-efficacy. Consistent with prior studies, we used a unipolar scale to measure self-efficacy [30]. For example, Vancouver and Kendall [48] used a unipolar scale with a single item to measure self-efficacy in a learning context. Bandura [60] has mentioned that bipolar scales are not appropriate to measure self-efficacy, and it should be measured with a unipolar scale [30].

4.2.4. Effort

We calculated team effort by taking the average of team members' effort. A team member's weekly effort was derived by taking the average of peer evaluation ratings that team members gave for his/her effort. All team members completed weekly peer evaluations where they rated each team member on multiple dimensions on a 5-point scale, effort being one of them.

4.2.5. Performance(t-2)

This is the lagged performance at time (t-2). We used (t-2) because the leaderboard displays the team ranks of $(t\text{-}2)^{th}$ week.

4.3. Control and other variables

4.3.1. $Effort_{T0}$, $Motivation_{T0}$, $Self\_efficacy_{T0}$

We included initial effort, initial motivation, and initial self-efficacy (i.e., lagged dependent variables at time T0) in the model to address issues of persistency. It is likely that, for most teams, these variables are correlated over time because of various historical factors, such as work ethic, ability, and other unobservable behaviors. The lagged dependent variable allows us to control for team-specific factors that might have been omitted.

4.3.2. Team size

This is the number of members in a team. Previous studies [64,65] have shown that team size has an impact on team performance.

4.3.3. Team skill

Prior studies have used average of team members' skill as a proxy for team skill [2]. Team skill score was operationalized as the average of the results of a pre-project test that all participants had to complete. The test measured each participant's technical literacy and proficiency, particularly with respect to his/her knowledge of and ability to use online collaboration tools (e.g., Dropbox, Google Docs, Doodle, project management tools such as Trello, Basecamp, and the like), working language proficiency (i.e., English), ability to work with information (e.g., reading comprehension, information recall, etc.), and basics of international business. We used the average score of the test as a covariate in the performance model for two reasons. First, prior studies have shown that performance is a function of participants' skill and efforts [56]. Second, this score is also an indication of their behavioral consistency. For instance, participants who scored well in the pretest are likely to perform well in the project because of factors such as their cognitive ability, motivation, and work ethic [30].

4.3.4. Clarity

This measures team members' perceived understanding of project requirements. Every week, the team members had to report their clarity level on a scale from 0 ("Nothing is clear and I do not know how to proceed”) to 100 (“Yes, everything is clear”). The weekly average of team members’ clarity score was used in the model. Prior studies have indicated that clear understanding of goals of a task has a positive influence on self-efficacy [66].

4.3.5. Enjoyment

We calculated the level of team enjoyment by taking the average of team members’ level of enjoyment with the project and the team at the end of each week. The question was how much they are enjoying working on the project with their team members, and the answers were on a scale between 0 (“Not enjoying at all”) and 100 (“Enjoying very much”). Reeve [67] mentioned that “enjoyment contributes to intrinsic motivation by sustaining the willingness to continue and persist in the activity” (p.83). In our context, when students enjoy working on the project with their teammates, they feel motivated to continue working hard on the project. Thus, enjoyment has an impact on motivation.

Prior studies have shown that self-efficacy and its effect on performance is moderated by task complexity [45]. We used similar tasks in both the competitive and non-competitive settings. Thus, task complexity would not impact our findings and is not included as a control variable.

Table 1, Table 2 summarize the descriptive statistics and correlation matrix, respectively.

Table 1. Descriptive Statistics.

	Competitive		**Noncompetitive**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Team Rank	48.48	25.92	48.73	29.14
Motivation	84.78	10.48	80.61	12.95
Self-Efficacy	85.26	9.41	82.51	10.43
Effort	4.13	0.46	4.07	0.45
Team Size	5.52	0.87	5.62	0.51
Team Skill	88.75	4.49	86.91	2.53
Clarity	83.94	10.66	82.63	11.84
Enjoy Team	85.50	10.00	82.19	12.32

Table 2. Correlation Matrix.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1 Team Rank	1.0000							
2 Motivation	−0.0902	1.0000						
3 Self-Efficacy	−0.1536	0.7875	1.0000					
4 Effort	−0.0404	0.4332	0.4270	1.0000				
5 Team Size	0.0447	−0.0609	−0.1217	−0.1160	1.0000			
6 Team Skill	−0.1475	0.1003	0.1394	0.1317	−0.1698	1.0000		
7 Clarity	−0.1203	0.7035	0.7706	0.4009	−0.1454	0.1021	1.0000	
8 Enjoy Team	−0.0724	0.8134	0.7516	0.4525	−0.0964	0.1208	0.6711	1.0000

5. Results

The analysis was conducted in two stages. First, we separately investigated the effect of self-efficacy on effort using the ordinary least square regression method. Then, we investigated the overall effect on performance employing a system of statistical models and using the seemingly unrelated regression (SUR) method [68] (more on this method later).

5.1. Self-efficacy and effort model

First, we investigated the direct and indirect impacts of team self-efficacy on team effort as indicated in following statistical model.

$$Effort_{it} = \alpha_0 + \alpha_1 Motivation_{ijt} + \alpha_2 Self\_efficacy_{ijt} + \alpha_3 Competition_j + \alpha_4 Self\_efficacy_{ijt} * Competition_j + \alpha_5 Effort_{ijT0} + \varepsilon_{ij} \tag{1}$$

where i, *j, t,* and *T0* denote teams, project (competitive or noncompetitive project), time period, and initial time, respectively; α_k ($k = 0 \ldots 5$) represents the coefficients of the variables.

Table 3 summarizes the results. Models 1 and Model 2 represent competitive and noncompetitive settings, respectively. Model 3 was tested using pooled data with a competition dummy variable to identify competitive (competition = 1) and noncompetitive (competition = 0) settings. The coefficient of self-efficacy is positive and significant in both Model 1 ($\alpha_2 = 0.022$, $p < 0.01$) and Model 3 ($\alpha_2 = 0.004$, $p < 0.1$) supporting Hypothesis 1 (H1).

Table 3. Ordinary Least Square Regression Results (Dependent Variable: Effort).

	Model 1 Competitive	**Model 2 Noncompetitive**	**Model 3 Pooled**
Self-efficacy (SE)	0.0216 ***	0.0031	0.0040 *
Motivation	0.0047	0.0097 ***	0.0087 ***
Competition			0.0275
SE*Competition			0.0137 ***
$Effort_{T0}$	0.1221 ***	0.1853 ***	0.1430 ***
R^2	0.3194	0.1368	0.2160

*** $p < 0.01$. * $p < 0.1$.

In Model 2, the coefficient of self-efficacy is insignificant. Moreover, in Model 3, the coefficient of the interaction effect of self-efficacy and competition is significant ($\alpha_4 = 0.014$, $p < 0.01$). Thus, Hypothesis 2 (H2) is supported. The results indicate that competition moderates the effect of self-efficacy on effort such that in a competitive environment the positive effect of participants' self-efficacy on their effort would be stronger than in a noncompetitive setting. In both Model 2 ($\alpha_1 = 0.010$, $p < 0.01$) and Model 3 ($\alpha_1 = 0.009$, $p < 0.01$), the coefficient of motivation is positive and significant supporting Hypothesis 4 (H4). The coefficient of motivation is not significant in the competitive setting. Moreover, the Sobel–Goodman mediation test showed that motivation acts as a partial mediator. The proportion of the direct effect of self-efficacy that is mediated through motivation is 17 percent in the competitive setting and 71 percent in the noncompetitive setting.

The variance inflation factor < 4. Thus, there is no evidence of multicollinearity in our model.

5.2. Self-efficacy and performance model

Based on our hypotheses, we formulated and tested the following statistical models:

$$Performance_{it} = \alpha_{10} + \alpha_{11}Effort_{it} + \alpha_{12}Skill_i + \alpha_{13}Size_i + \varepsilon_{1i} \tag{2}$$

$$Effort_{it} = \alpha_{20} + \alpha_{21}Motivation_{it} + \alpha_{22}Self_{efficacy_{it}} + \alpha_{23}Performance_{i(t-2)} + \alpha_{24}Effort_{iT0} + \varepsilon_{2i} \tag{3}$$

$$Motivation_{it} = \alpha_{30} + \alpha_{31}Self\_efficacy_{it} + \alpha_{32}Enjoy\_team_{it} + \alpha_{33}Motivation_{iT0} + \varepsilon_{3i} \tag{4}$$

$$Self\_efficacy_{it} = \alpha_{40} + \alpha_{41}Performance_{i(t-2)} + \alpha_{42}Clarity_{it} + \alpha_{43}Self\_efficacy_{iT0} + \varepsilon_{4i} \tag{5}$$

where i, j, t, and T0 denote teams, project (competitive or noncompetitive project), time periods, and initial time, respectively; $\alpha_{1,2,3,4,k}$ ($k = 0\ldots4$) represents the coefficients of the variables.

We used SUR as our main estimation method for two reasons. First, because self-efficacy impacts performance (through motivation and effort) and past performance plays a role in shaping self-efficacy and effort, these variables are expected to be driven by some common observable and unobservable factors. It is likely that some unobservable factors or omitted variables are included in the error terms of the multiple equations. Thus, the error terms of these equations can be correlated. In fact, the Brusch–Pagan test statistic confirmed that there is a signifcant correlation among error terms ($p < 0.05$). Therefore, we followed Zellner's [68] approach to estimate an "SUR" that allows correlated errors. It involves a consistent and an efficient estimation procedure [69]. Second, even though this set of equations looks like a simultaneous equation system, the simultaneity is unlikely due to the following reasons. The *performance* variable is lagged in the *effort* equation, and there is no direct feedback between Eqs. (2) and (3). Moreover, all the explanatory variables in Eq. (5) do not have a direct feedback loop with any other dependent variables in the system. Therefore, endogeneity due to simultaneity does not seem to be an issue because the dependence is not bi-directional.

As the data were drawn from two separate samples, we ran models seperately for the competitive and non-competitive settings. This also simplifies the data analysis process. Table 4 summarizes the results for the competitive setting. In the effort model, the coeficient of self-efficacy ($\alpha_{22} = 0.023$, $p < 0.01$) and motivation ($\alpha_{21} = 0.007$, $p < 0.1$) is positive and significant. Thus, Hypothesis 1 (H1) and Hypothesis 4 (H4) are supported. Results show that high self-efficacy leads to high effort in the competitive setting. In the motivation model, the coefficient of self-efficacy is positive and significant ($\alpha_{31} = 0.672$, $p < 0.01$). Thus, Hypothesis 3 (H3) is supported. This implies that high self-efficacy improves solver motivation in the competitive setting. In the performance model, the coefficient of effort is negative and significant ($\alpha_{11} = -10.037$, $p < 0.01$). The coefficient is negative because our performance scale is reversed, i.e., a lower value means higher performance. Thus, Hypothesis 5 (H5) is supported. Thus, in a competitive setting, high solver self-efficacy leads to better performance through increasing effort, thereby supporting the view of the self-efficacy theory. In the self-efficacy model, the coefficient of performance$_{(t-2)}$ is negative and significant ($\alpha_{41} = -0.045$, $p < 0.01$). Thus, Hypothesis 6 (H6) is supported, which shows that interim performance is a strong determinant of self-efficacy. To confirm these results, we conducted the Sobel–Goodman mediation test. Test results reinforced the finding that self-efficacy significantly mediates (approximately 78%) the impact of past performance on effort.

Table 4. Seemingly Unrelated Regression Results (Competitive-Setting).

	Self-Efficacy	**Motivation**	**Effort**	**Performance**
$Performance_{(t-2)}$	−0.0451 ***		−0.0018 *	
Effort				−10.0372 ***
Skill				−0.9204 **
Self-Efficacy		0.6725 ***	0.0231 ***	
Motivation			0.0071 *	
Clarity	0.6894 ***			
Enjoy Team		0.3660 ***		
Size				−0.8193
$Effort_{T0}$			0.1468 ***	
$Motivation_{T0}$		0.0038		
$Self\_efficacy_{T0}$	0.0712			

Note: performance scale is reversed, i.e., a lower value means higher performance.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

Table 5. Seemingly Unrelated Regression Results (Noncompetitive Setting).

	Self-Efficacy	**Motivation**	**Effort**	**Performance**
$Performance_{(t-2)}$	−0.0187 **		−0.0002	
Effort				6.6875
Skill				−0.0270
Self-Efficacy		0.2933 ***	−0.0067 **	
Motivation			0.0151 ***	
Clarity	0.6284 ***			
Enjoy Team		0.6929 ***		
Size				−2.9300
$Effort_{T0}$			0.2274 ***	
$Motivation_{T0}$		0.03215		
$Self\_efficacy_{T0}$	0.2077			

Note: performance scale is reversed, i.e., a lower value means higher performance..
*** $p < 0.01$. ** $p < 0.05$.

Table 5 summarizes SUR results for the noncompetitive setting. Interestingly, in the effort model, the coefficient of self-efficacy (α_{22} = - 0.007, $p < 0.05$) is negative and significant. It implies that high self-efficacy leads to low effort in a non-competitive setting, supporting the view of the control theory. High self-efficacy indicates that the participants believe the results in the current state are closer to the goal and they exert less effort [30]. Thus, our results show that competition moderates the relationship between self-efficacy and effort, providing further support for Hypothesis 2 (H2). Similar to the competitive setting, the relationship between self-efficacy and motivation is positive, and so is the relationship between motivation and effort. These results provide further support for Hypothesis 3 (H3) and Hypothesis 4 (H4). Interestingly, the results also show that high past performance leads to high self-efficacy supporting Hypothesis 6 (H6). We also found that the direct effect of past performance on self-efficacy is significantly higher in the competitive setting than in the non-competitive setting. Furthermore, the direct effect of past performance on effort is significant in the competitive setting but is not significant in the noncompetitive settings. Collectively, these results show that leaderboard feedback helps to induce recursive relationships in the competitive setting. That, in turn, will help enhance the overall performance through increasing effort. Table 6 provides a summary of the results.

Table 6. Summary Results.

Hypothesis	Competitive	Noncompetitive	Pooled	Results
H1: Self-efficacy → Effort (+)	(+)	(-)	(+)	Partially supported
H2: Competition Moderation (+)			(+)	Supported
H3: Self-efficacy → Motivation (+)	(+)	(+)		Supported
H4: Motivation → Effort (+)	(+)	(+)	(+)	Supported
H5: Effort → Performance (+)	(+)	n.s.		Partially supported
H6: Int. Performance → Self-efficacy (+)	(+)	(+)		Supported

(+) positive relationship; (-) negative relationship; n.s. nonsignificant relationship.

We also plotted the interaction effect of competition on the self-efficacy and effort relationship (Fig. 3). The interaction plot clearly shows that effort is positively related to self-efficacy in the competitive setting while it is negatively related in the non-competitive setting. That is, in competitive setting when self-efficacy increases, the solvers exert more effort while in noncompetitive setting when self-efficacy increases, the solvers reduce their effort. In Fig. 3, the Y-axis represents net effort (i.e., Effort- EffortT0) and X-axis shows self-efficacy. The X-axis begins at 40 because the minimum self-efficacy in the competitive setting was 40.

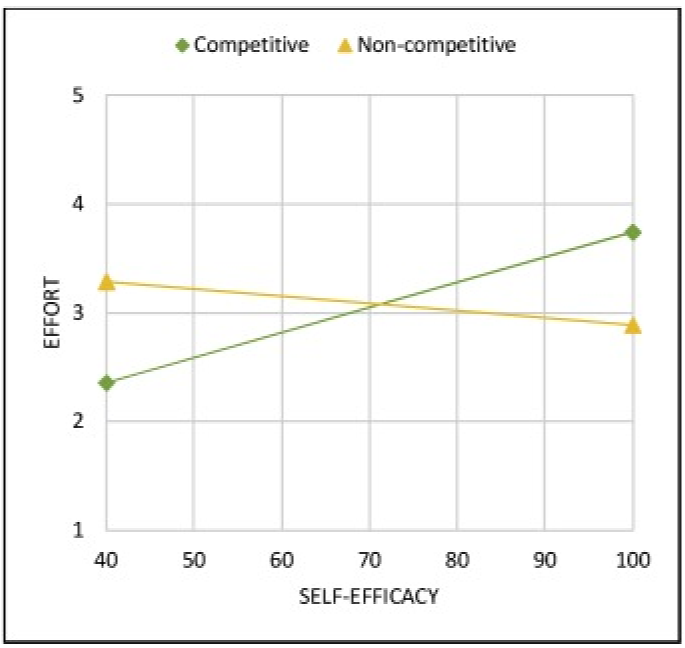

Fig. 3. Interaction of Competition with Self-Efficacy and Effort.

5.3. Robustness tests

Estimations are generally more efficient when equations are estimated together as a system. There are two kinds of joint-system estimations: SUR [68] and three-stage least squares (3SLS) [70]. 3SLS would be more appropriate when there is a system of equations with endogenous regressors. Our regressors could be endogenous because of omitted variable bias. For example, some unobservable factors such as team members' work ethic and abilities could impact regressors such as performance and efforts. Therefore, we also used 3SLS to estimate the coefficients. Consistent with the finding of the main model and affirming the robustness of our results, 3SLS results showed that competition moderates the relationship between self-efficacy and effort. Tables 7 and 8 summarize 3SLS results for competitive and noncompetitive settings, respectively.

Table 7. 3SLS Regression Results (Competitive Setting).

	Self-Efficacy	Motivation	Effort	Performance
$Performance_{(t-2)}$	−0.0440 ***		−0.0025 **	
Effort				−18.7303 ***
Skill				−0.7976 **
Self-Efficacy		0.7256 ***	0.0296 *	
Motivation			0.0018	
Clarity	0.6820 ***			
Enjoy Team		0.3732 ***		
Size				−1.8283
$Effort_{T0}$			0.1449 ***	
$Motivation_{T0}$		−0.0025		
$Self\_efficacy_{T0}$	0.0521			

Note: performance scale is reversed, i.e., a lower value means higher performance.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

Table 8. 3SLS Regression Results (Non-competitive Setting).

	Self-Efficacy	Motivation	Effort	Performance
$Performance_{(t-2)}$	−0.0159 *		−0.0008	
Effort				14.8893
Skill				−0.0282
Self-Efficacy		0.2883 ***	−0.0190 ***	
Motivation			0.0268 ***	
Clarity	0.6230 ***			
Enjoy Team		0.6714 ***		
Size				−2.8677
$Effort_{T0}$			0.2015 **	
$Motivation_{T0}$		0.0160		
$Self\_efficacy_{T0}$	0.2160 ***			

Note: performance scale is reversed, i.e., a lower value means higher performance.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

6. Discussion

As research advances are being made in the field of crowdsourcing, interesting insights have emerged about improving the performance of crowdsourcing teams (see [2,14]). These insights suggest that both task-design and solver characteristics can influence crowdsourcing performance. Building on these insights, we examined how in competitive crowdsourcing tasks, self-efficacy, effort, and subsequently performance are related. Theoretical support for the self-efficacy and effort/performance relationship comes from the long-standing debate in the self-efficacy literature about the conflicting nature of this relationship (see [26,30,71]). In the following sections, we review key research findings, implications for theory and practice of crowdsourcing, limitations, and provide future research directions.

6.1. Key findings and theoretical implications

Our first three research questions are: *How does competition impact the self-efficacy and effort relationship in Crowdsourcing Teams? Does motivation mediate the self-efficacy and effort relationship? Does self-efficacy predict effort and subsequent performance?*

The first set of results demonstrates that competition moderates the relationship between solver self-efficacy and effort. Thus, in crowdsourcing competitions, high solver self-efficacy leads to increased solver effort. Results also suggest that solver motivation partially mediates this relationship and that solver effort further mediates the relationship between self-efficacy and performance. These findings imply that in crowdsourcing competitions, high solver self-efficacy improves crowdsourcing performance through improved motivation and effort. These findings are consistent with the tenets of self-efficacy theory, which focuses on continuous improvement of performance through discrepancy-creation, and generally predicts a strong, positive effect of self-efficacy on performance [27,30]. Specifically, solvers with high self-efficacy set higher goals than that with low self-efficacy. Discrepancies created via goal-setting typically improve solver motivation and makes them exert increased effort to achieve their goals [30,72,73]. This explains the strong, positive effect of self-efficacy on performance.

Interestingly, while the results suggest a positive self-efficacy and effort relationship in competitive settings, a contradictory relationship is observed in the non-competitive setting. Specifically, self-efficacy leads to *reduced* effort in noncompetitive settings. The results also show that motivation mediates the relationship between self-efficacy and effort. These results emphasize the role of discrepancy-reduction in restricting an individual's progress toward established goals, and align with the tenets of control theory [30,61,74]. Specifically, solvers holding optimistic beliefs (i.e., high self-efficacy) might perceive their current state as closer to their goals than what it is in reality [30]. This state of reduced discrepancy lowers their motivation, and results in less effort being applied toward goal achievement, than when self-efficacy is low [48]. To summarize, in non-competitive settings, the negative effect of self-efficacy on effort is a result of solvers' self-efficacy beliefs being inflated relative to their actual goal progress.

Overall, this pattern of results suggests that the relationship between solver self-efficacy and performance is moderated by the competitive setting among crowdsourcing teams. This is a key theoretical contribution, as it helps reconcile two opposing views in the self-efficacy literature. Socio-cognitive theorists support the view that self-efficacy is positively related to performance [27], while control theorists support the view that self-efficacy is negatively related to performance [28]. In competitive settings, the positive effect dominates, supporting the self-efficacy theory. However, in noncompetitive settings, results suggest a negative effect on effort, supporting the control theory. While past research has identified task complexity as one possible contingency for positive/negative results [28], we make additional contribution by suggesting crowdsourcing competitions as yet another context to reconcile the ongoing debate between the two groups of theorists.

The moderating role of competition highlights another theoretical contribution of the study. It extends the application of social comparison theory to explain the self-efficacy and effort relationship in crowdsourcing competitions. It seems that competition among crowdsourcing teams heightens solvers' tendencies to self-evaluate by comparing themselves to others [19]. This happens as a result of two key characteristics of the competition: monetary reward and interim performance feedback via team rankings on the leaderboard. Commensurate to the social comparison perspective, achieving a top-rank to win the monetary reward acts as a meaningful standard for solvers. Interim performance feedback further encourages competition by facilitating social comparison among solvers. Performance feedback also interacts with participants' high self-efficacy to facilitate positive discrepancy-creation, further encouraging upward comparisons, and motivating them to achieve better or targeted ranks in light of their past performance. High self-efficacy also motivates them to exert extra effort to achieve these goals. Thus, competition eventually improves overall performance of the crowdsourcing teams.

The salience of these results is further highlighted by the results from the non-competitive setting. Solvers in this setting were neither offered monetary reward for achieving a top rank nor given any interim performance feedback. It seems that, in the absence of a monetary incentive to achieve top-rank, solvers lack any meaningful standard to compete for [6]. The lack of interim performance-feedback prevents social-comparison among participants and contributes to create a state of discrepancy-reduction. Specifically, in the absence of performance feedback, participants with high self-efficacy are overly optimistic about their current state of goal achievement (vis-à-vis other teams). The reduced discrepancy, combined with an absence of a meaningful standard and no social comparison, reduces their motivation and effort toward their goal progress.

Our fourth research question is: Do self-efficacy and performance share a *recursive relationship*?

Our results also demonstrate that past performance predicts self-efficacy in both competitive and non-competitive settings. Thus, self-efficacy and performance share a recursive relationship, i.e., self-efficacy acts as a *predictor* of future performance as well as an *outcome* of past performance. The positive effect of past performance on self-efficacy in competitive settings results from solvers using performance-feedback to judge their ability to achieve top rankings in the future [27,30,75]. Solvers in competing teams specifically compare feedback on past performance to their goal level to assess goal-performance discrepancies [61]. High past performance is indicative of goal-performance discrepancies, which, in turn, increases self-efficacy [30]. A different dynamic seems to be working in the noncompetitive setting. Because performance-feedback was not available in this setting, solvers may have thought about past performance on similar tasks, which may have affected their self-efficacy [27,76].

These implications add yet another link to connect the two opposing theoretical frameworks related to the self-efficacy and performance causality. Control theorists have suggested that the positive relationship between the two is created by the effect of past performance on self-efficacy, and not vice-versa [31]. This challenges the classical belief that self-efficacy predicts performance [77]. Our results show that the self-efficacy-performance relationship is an interesting amalgamation of both aspects and that self-efficacy and performance share a recursive relationship. Additionally, results also show that adding gaming technologies, such as a leaderboard, significantly impacts the recursive relationship in the competitive setting. In other words, the use of gaming technologies leads to a stronger recursive relationship between self-efficacy and performance in competitive settings than those in non-competitive settings.

6.2. Managerial recommendations

In addition to the theoretical contributions, the findings of this study provide several practical recommendations for crowdsourcing seekers, solvers, and platform providers. Improving team performance by enhancing the solution quality is important for all three parties. Seekers can find better solutions to their business problems, and platform-providers can attract more seekers to their platforms and enhance their revenue through platform charges (typically, platform-providers charge a fee from seekers for hosting and assisting their contests). Solver teams can increase the chances of winning the reward by effectively allocating effort and improving solution quality.

Our findings provide insights to platform providers about designing platforms that increase the likelihood of receiving high-quality solutions. For example, the findings can help platform-providers design platforms that motivate and engage participants throughout the contests. Specifically, it provides insights on how to demand solvers' best effort by inducing competition through reward structures combined with open leaderboard feedback.

Second, platform providers should also communicate to the seekers the benefits of holding crowdsourcing competitions, especially if the seekers are looking for high-quality solutions to their business problems. On the other hand, if the seekers are there only for the sake of information-gathering, then low-stakes, non-competitive settings may be sufficient. To advertise the benefits of each setting more effectively, a forum could be established for seekers to share their experiences with competition and non-competition settings. Embedding such information-sharing mechanisms would also help solvers decide which setting they would prefer. In addition, platform providers can utilize the findings to create a multitiered revenue model. Specifically, seekers pay higher fees for using platforms that support competitive tasks by using gaming technologies, such as open leaderboard feedback systems. Other seekers, which are running non-competitive tasks, pay lesser fees for using simpler platforms.

Third, our results provide insights to solver teams about the underlying reasons for their own behaviors, and for the behaviors of their competitors. These insights can be helpful when teams decide how to allocate effort in competitive settings to win the reward. For example, in many crowdsourcing contests, multiple teams typically end-up merging with each other to combine effort and improve performance. The insights from this study would help teams evaluate other teams, in light of their competitive behaviors, prior to a merger.

6.3. Limitation and future research

The findings of this study should be interpreted in the context of its limitations. Understanding these limitations also create opportunities for future studies. First, different from some crowdsourcing settings, our teams were not self-organized. The platform intervened in the process of forming teams. Therefore, the generalizability to other forms of crowdsourcing is limited. Future studies could study crowdsourcing platforms, such as TopCoder and InnoCentive, to examine how the self-efficacy-effort-performance relationship is enacted. Nevertheless, our findings may be generalizable to these platforms to the extent that they offer similar task-design settings, such as competition and non-competition. Second, the X-Culture platform uses unipolar scales with single items to measure some latent constructs. While multiitem scales may be preferred by some, many have used single items in the prior literature [30,48]. Third, our experiment subjects were students. However, this demographic is platform-specific, and prior studies in self-efficacy literature have also used student-centric data [26,51]. All the same, our subjects worked on finding actionable solutions to real-world problems for active business organizations. Thus, it would be worthwhile to examine results in other crowdsourcing settings with different types of solvers. Fourth, our study only compares competitive and non-competitive settings. Some crowdsourcing platforms also facilitate inter-team collaborations. In future studies, it would be interesting to investigate how the effects would change in a collaborative setting, or even in a hybrid setting where non-competition, competition, and collaboration co-exist.

7. Conclusion

Crowdsourcing teams are increasingly helping organizations find creative solutions to their pressing problems. Competition is a key characteristic in crowdsourcing teams. In this study, we developed a model based on socio-cognitive theory and control theory to investigate the impact of competition on the nature of self-efficacy and effort/performance relationship in crowdsourcing teams. We found that self-efficacy has a positive effect on effort and subsequently performance in competitive settings, while self-efficacy negatively affects effort in noncompetitive settings. While speculated by many, we were also able to confirm the recursive relationship between self-efficacy and performance. These findings not only contribute to the self-efficacy literature by providing deeper explanations for the mixed findings on self-efficacy and performance relationship but also provide new insights to crowdsourcing theory and practice. It is an important and noteworthy step toward enabling crowdsourcing providers to design platforms that will engage and motivate seekers to perform better.

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