Being a Solo Endeavor or Team Worker in Crowdsourcing Contests? It is a Long-term Decision You Need to Make

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Workers in crowdsourcing are evolving from one-off, independent micro-workers to on-demand collaborators with a long-term orientation. They were expected to collaborate as transient teams to solve more complex, non-trivial tasks. However, collaboration as a team may not be as prevalent as possible, given the lack of support for synchronous collaboration and the "competition, collaboration but transient" nature of crowdsourcing. Aiming at unfolding how individuals collaborate as a transient team and how such teamwork can affect an individual's long-term success, this study investigates the individuals' collaborations on Kaggle, a crowdsourcing contest platform for data analysis. The analysis reveals a growing trend of collaborating as a transient team, which is influenced by contest designs like complexity and reward. However, compared with working independently, the surplus of teamwork in a contest varies over time. Furthermore, the teamwork experience is beneficial for individuals in the short term and long term. Our study distinguishes the team-related intellectual capital and solo-related intellectual capital, and finds a path dependency effect for the individual to work solely or collectively. These findings allow us to contribute insights into the collaborative strategies for crowd workers, contest designers, and platform operators like Kaggle.

CCS Concepts: • **Human-centered computing** → **Empirical studies in HCI**; **Empirical studies in collaborative and social computing**.

Additional Key Words and Phrases: Crowdsourcing; Team Worker; Solo Endeavor; Long-Term Aspect; Transient Team; Kaggle; Crowdsourcing Contests

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1 INTRODUCTION

Crowdsourcing[1] has been rapidly growing over the past decade, which has reformed how work is conducted and delivered for individuals and organizations [46, 59, 85, 98, 109]. Organizations

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[1]Following [28, 85], this study considers crowdsourcing as *"is a type of participative online activity in which an individual, organization, or company with enough means proposes to a group of individuals of varying knowledge, heterogeneity, and number, via a flexible open call, the voluntary undertaking of a task"*. Therefore, the online labor markets such as Upwork.com, PeoplePerHour.com, Fiverr.com, Freelancers.com and crowdsourcing contests such as Kaggle.com, TopCoder.com, HackerOne.com, Dell IdeaStorm are all considered as crowdsourcing platforms.

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choose crowdsourcing to reach external knowledge and skills for brand visibility, solution diversity, and cost reductions [34, 122]. Millions of crowd workers increasingly turn to online crowdsourcing platforms to access work [12], demonstrated by an average of 20% growth every year [21, 58].

Recently, the crowd workers are shifting from one-off, independent micro-workers to on-demand, skilled collaborators with a long-term orientation [27, 41, 43, 46, 85, 109, 125]. Some studies have investigated the motivations [10, 73], sustained participation [7, 13, 89], skill development [3, 46, 47, 100] and career trajectories[12, 96] of these professional crowd workers. Unlike the micro-workers who focus on short-term, small-sized works with low requirements on specialized skills [62], these skilled workers often need to engage in longer and more complex projects requiring collaboration synchronously with others [74].

However, the current model of crowdsourcing platforms is insufficient to support the collaborations among workers [62]. Crowd workers typically complete their tasks independently by design: Their jobs are allocated by algorithms and controlled by organizations, and the in-app communication among crowd workers are not encouraged by the platforms [52, 110]. This presents significant obstacles to workers' collective organizing [110] and constrains their creativity and autonomy [84]. The subsequent isolation further limit the experience sharing, undermines the social support[21, 99], and amplifies race and gender biases [4, 31, 40, 123].

As the socialization problem and lack of interaction in collaborative platforms became evident, the CSCW community started discussing how team formation[41], coordination[93], and collaboration[87] could support teams successful in collaborative platforms. Some crowdsourcing platforms [5, 49, 53, 116] structure tasks as contest where people can form transient teams to develop solutions and compete for the provided rewards. New crowdsourcing techniques have been implemented to nurture and support constructive social dynamics [95, 106, 112]. Some studies focus on examining the factors that can influence teams performance, including contest-specific factors (e.g., reward structure [5], project duration and complexity [120]), individual-specific factors (e.g., individual roles and strategy [24, 55]), team-specific factors (e.g., team diversity [9, 69, 88, 89, 92, 105, 115] and team capability [19, 35, 44, 61]), and environment features (e.g., communication mechanisms [53, 77, 102] and geographical distance [107].)

However, collaboration as a team in crowdsourcing contests may not be as prevalent as expected [49, 53, 124]. First, recent studies [1, 8, 71, 80] in collective intelligent show that social influence can increase the individual similarity which compromise the independence assumption to achieve the "wisdom of crowds" [101], resulting into conflicting observations regarding the benefit of social interactions [8, 11, 54, 64, 71, 77, 80, 81, 117]. In another word, working as a team should not be a straightforward strategy. Second, while teams can leverage the different skills and perspectives of their members, they need to overcome challenges in coordination which are much more significant in crowdsourcing contests [38, 45, 55, 65, 118]. As crowdsourcing teams are much shorter-lived encounters with higher coordination costs, working as a team is not necessarily a better option than being a solo endeavor [17, 49]. Sometimes even high-performing teams can be miserable [18]. Researchers find that collaboration happens at a shallow level on the platform, and only few individuals choose to collaborate [70, 83, 102, 124]. Third, most studies on team performance assume that the transient teams have been formed, so few studies start to investigate different team formation strategy and its impacts on the team formation process and its performance [42, 60, 72, 93, 94, 106, 111]. Additionally, the transient teams are usually formed for a specific contest, while the sustained participation of individuals is critical for the success of the crowdsourcing platform [18, 86, 89]. Individuals are incentivized by the long-term success in the platform, which needs the balance between the competitive outcomes and cooperative behaviors [33, 104]. While existing studies focus on the immediate outcome of the transient team, the effect of the teamwork experiences on an individual's long term performance, however, are largely lacking.

Therefore, while the working style in crowdsourcing shifts from one-off, independently working to long-term, synchronous team collaboration, collaboration as a team in crowdsourcing contests is not intuitive. As less is known about what motivates crowd workers to collaborate with each other as a team and whether working in a transient team can be helpful for individuals' long-term success, this study aims to answer the following four exploratory research questions:

- *RQ1*: Does working as a team is becoming a trend in crowdsourcing contests?
- *RQ2*: Is working as a team always a good choice? If not, under what conditions is?
- *RQ3*: How do the cumulative teamwork experiences affect individuals' short-term and long-term performance?
- *RQ4*: What factors motive participants to work as a team?

We conducted an empirical study with Kaggle–one of the prominent, and the *de facto* blueprint, crowdsourcing contest platform for non-trivial data analysis and predictive modeling. On Kaggle, each user can participate alone or team up with other members (who can be stranger) to join a contest. The team is transient, and for each contest, individuals need to reform a new team even if they have the same team members. This provides us an ideal environment to investigate how individuals decide to work independently or collaboratively.

Our results reveal several key signals of working as a transient team:

- There is a growth in the average proportion of working as a transient team. Moreover, both complexity-related and incentive-related designs of contests play an essential role in affecting the proportion of working as a transient team. As contests become more complex (i.e., shorter contest time, larger data size, and without kernel system), there would be more teamwork while the increasing contests extrinsic incentives (i.e., size of the reward) would reduce the teamwork.
- From a static perspective, working as a transient team is correlated with better performances in terms of medals and submissions but worse performances in terms of points. Additionally, from a dynamic perspective, while the average amount of submissions increases, the benefits of the average amount of medals for teamworks decrease over time.
- We further find that teamwork experiences are associated with both better individual short-term performance (i.e., the points and medals individuals' gained in a contest) and long-term performance (i.e., the cumulative number of points and medals over many contests).
- Analysis from a micro point of view reveals several exciting patterns on how participants' intellectual capital and structural position within collaboration networks affect teamwork choice. We distinguish the team-related intellectual capital and solo-related intellectual capital. The empirical evidences reveal a positive association between the level of teamwork-related intellectual capital and the likelihood of the participant deciding to work as a team. On the contrary, there is a negative association between the level of solo-related intellectual capital and the participant's likelihood of working as a team. The influence of intellectual capital becomes stronger as the intensity of past collaboration ties increase. This reveals a path dependence effect when crowd workers decide to work collaboratively or solely.

These findings have direct implications for multiple stakeholders within crowdsourcing contests:

- We provide crowd workers with actionable insights that can help them to improve their short-term and long-term performance.
- We provide contest organizers who want to incentivize collaboration with several cues. Contest organizers can take steps to design the complexity and incentives of the contest to promote collaboration.
- We uncover several cues that platforms may look for, including remedying the penalty on teamwork like Kaggle's exiting point system, encouraging participants and contest organizers

to access a kernel system like Kaggle Kernels, as well as empowering the team collaboration capability for such kernel systems. Importantly, platforms should be aware of the path dependence effect for working collaboratively or solely. To break such an effect, improving the teamwork experiences, especially for those solo endeavors, could be beneficial.

The rest of the paper is structured as follows. Section 2 reviews the related work on evolution trends of crowdsourcing and the transient team collaboration. Section 3 details the design of our studies. Section 4 describes the Kaggle platform and data as the empirical context for this study. Section 5 reports our result. Section 6 summarizes this study with an in-depth discussion about the implementations and the limitations.

2 RELATED WORK

As shown in Figure 1, to identify the research gap and the position of this study, we first review the studies focusing on evolution trends for the crowdsourcing platform, including the long-term development and synchronous collaboration. Then, we summarize the works related to the transient team collaboration, including team performance and team formation strategy.

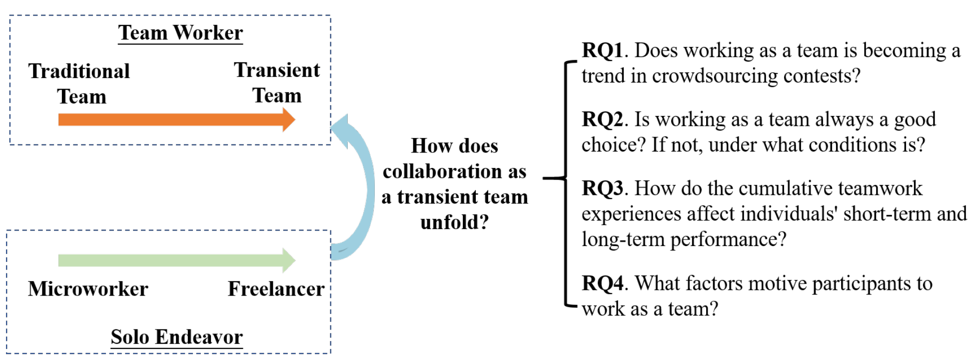


Fig. 1. The Research Gap: From Solo Endeavor To Team Worker?

2.1 The long-term orientation of crowdsourcing

Crowdsourcing was considered a one-off undertaking in the early days, where microtask was the primary form of work exchanged on platforms like Amazon's Mechanical Turk [46]. With the increasing involvement of highly skilled crowd workers in the crowdsourcing platform, recent studies have highlighted the longer-term orientation for these crowd workers working on more professional tasks [12, 27, 85].

Compared with microworkers who work on temporal microtask, professional crowd workers are more self-regulated and learning-oriented [73]. They are motivated by learning new skills incrementally to obtain better performance in the future [12, 108]. Developing a skill related to a worker's existing skill set correlates with better performance of the new skill [46]. Hence, like they did offline, online workers can structure their career, forming some pretty stable career paths that may enable linear career progression [96]. A recent study shows that crowd workers in Nigeria transition and transform crowd work into long-term employment [27] and there is an organizational trend for the vulnerabilities hunters [47].

The sustained participation and long-term success, which a crowd worker returns for additional works or competitions, has attracted significant attention. Fang et al. [29] reveal that situated learning and identity construction are associated with sustained participation. The positive feedback can increase the workers' perceived pride and respect, encouraging them to return for other competitions [14]. The number of comments and the size of the peers' groups can indicate whether the new contributors can become long-term contributors [127].

However, the performance of long-term and sustained participation in crowdsourcing varies. For example, workers with diverse skills earn higher wages than those with more specialized skills [3]. While the social capital can be beneficial for the long-term engagement, women can be at a disadvantage in teams lacking diversity in expertise [89]. Workers indeed expand the range of skills that they provide overtime and who expand into a new skill that is highly related to their existing skills complete such expansion faster and also perform better on the new skill [46], the marginal utility for them to develop new skills also diminishes [47] and the number of existing skills can negatively influence the performance of new skills [46]. The serial ideators will contributes solutions similar to their previous successful ideas, resulting into a negative effects from the past successes [7]. Other studies show that individuals who performance well in the previous competition can be more likely to participate again and gain better performance in the subsequent contests [44].

This stream of research confirms the shift from a one-off perception of crowdsourcing to long-term orientation. However the impact of such evolution is still inconclusive. More research is needed to advance our knowledge of how these long-term-oriented professional crowd workers act, collaborate, grow and become successful in the crowdsourcing platform.

2.2 From isolation to synchronous collaboration

With the shifting to long-term participation, highly skilled crowd workers need to collaborate to solve more complex tasks synchronously. However, the current model of crowdsourcing platform is insufficient to support such a synchronous collaboration [62]. Crowd workers typically complete their tasks independently by design as their jobs are allocated by algorithms and the in-app communication among them are not encouraged by the platforms [52, 110]. For the microtasks, workers can complete them independently and rarely collaborate. However, many tasks worth completing require cooperation between the crowd workers with their clients and among each other. Recent investigations on the existing crowd-writing systems [30] reveal that writing with the crowd requires significant system design attention, like the monitoring process, to the worker as a person and how workers engage with each other and the writing tasks collectively. This reaffirms the importance of considering workers holistically when developing crowd-powered systems for complex domains and highlights the advantaged understanding of the collaborative actions among crowd workers [50, 78].

Additionally, the lack of effective collaborations among workers, presents significant obstacles to workers' collective organizing [110], constrains their creativity and autonomy [84], limits the experience sharing and perceived social support [21, 56, 99], and amplifies race and gender biases [4, 31, 40, 123]. Workers find it difficult to understand how their activities fit within a broader picture and relate to other workers [110]. The lack of meaningful social and collegial relationships in the workplace also prevents workers from providing the necessary emotional support [56]. While online communities such as social media groups have presented the potential to facilitate information exchange, emotional support, group social identities forming, coordination, and collective action among crowd workers [51, 68, 99, 113], factors such as difficulties in assessing other workers' sentiments and activities, the competitive nature of crowd work, the diversity among workers, and their portrayal as independent contractors prevent that from happening [121].

This stream of research reveals an urgent requirement to investigate the synchronous collaborations among crowd workers. Our knowledge of motivating and supporting the synchronous collaboration among crowd workers are still limited.

2.3 Performance for collaboration as teams

Researchers are increasingly investigating team performance within a crowdsourcing contest, where ad-hoc teams are formed by strangers for short-lived purposes, to provide solutions and competitive for the provided rewards [55]. Crowdsourcing contests have become an important area that organizations rely on to receive high-quality ideas and solutions from the crowd [23, 35]. Therefore, many studies have been developed to describe the factors that can affect the outcomes after teams have been formed, including:

(1) *Task/contest-specific factors* such as reward, task type, task complexity and contest duration [5, 17, 36, 120]. For example, Yang et al [120] found that contests obtained more submissions when they had a longer duration and were less complex. When contests had higher monetary rewards, more people entered the contest but fewer submitted final work. Martinez [36] shows that the contest complexity and autonomy, task variety, and knowledge characteristics can affect the quality and number of submissions.

(2) *Individual-specific factors* such as individuals' intrinsic motivation, strategy, experience and roles [2, 24, 32, 55, 66, 76, 88]. Dissanayake [24] investigated the allocation of members' social and intellectual capital within a virtual team, showing that a member's social and intellectual capital on team performance varies depending on his or her roles. Jiang et al. [55] reveals that individuals' different working styles and preferences can contribute to teamwork differently, especially in challenging and competitive environments.

(3) *Team-specific factors* such as team diversity in terms of team structures[82, 92, 115, 128], gender [89, 105] and demographic [9], team capability including social capital [24, 35, 44] and collective intelligence [19, 61], and team culture such as collaboration atmosphere [18, 53, 60, 94]. For example, teams on Kaggle composed of skilled members and with leaders socially connected to the community did better than others [24]. The number of social ties a crowd member has is positively related to the number of votes an idea receives[44]. The dynamic adaption of team structure based on observable feedback can result into a better performance[128]. Team's discussion-forum performance and solution-sharing performance also have significant effect on its competition performance[53]. The active engagement with others' ideas is a crucial signal of a viable team [18].

(4) *Environment-specific factors* such as the online environment, competition intensity, collaboration and communication channel [16, 24, 77, 102]. For example, Boudreau and Lakhani [16] showed that the crowd in the open design condition, where all submitted code made publicly available during the contest, can produced better-performing code but fewer people participated. Additionally, the intensity of the contest moderates individual's influence on the final performance [24]. Tausczik et al. [102] investigated the community-level sharing of codes on Kaggle, showing that sharing code improved individual, but not collective performance. Based on a series of 256 Web-based experiments, in which groups of 16 individuals collectively solved a complex problem and shared information through different communication networks, Mason and Watts [77] emphasized the importance of effectively spreading the solutions throughout the communication network.

While this stream of research provides fruitful insights on what makes teams successful, they place more emphasis on describing what happens after teams were formed and build on the assumption that collaboration as a team is beneficial. However, the competitive nature of the contests [53, 124] and members in transient teams are short-lived encounters [55], may reduce the frequency of substantive, valuable collaboration [118]. The study [17] on an online German design contest identified two distinct sets of users where one collaborates for curiosity, and others' recognize good work done by others, helping others, and learning from others, while the other does not as these users have a more precise goal and focus on their own idea. Hutter et al. [49] also reveals that a variety of collaboration strategies within contests where some exclusively competitive, some exclusively cooperative, and some a combination of the two. The study on the Stack Overflow and a discussion mailing list for R community reveals that Stack Overflow is less collaborative than mailing lists because of its competitive nature [124]. Additionally, researchers find that while collaboration may improve performance, it happens at a low level[70, 83].

Hence, collaboration as a team in the crowdsourcing contest may not be an intuitive strategy as expected. The observation of relative low-level collaboration in real crowdsourcing contests [17, 70, 83], and the mix outcome of social interactions within team collaboration [8, 11, 54, 64, 71, 77, 80, 81, 117], both suggest more empirical studies to advance our understanding of how collaboration as a team can happen and what can encourage teamwork.

2.4 Team formation strategy and its dynamic

While most studies on team performance assume that teams have been assembled, some recent studies [37, 41] start to investigate the team-assembly strategy. Team dating, where people interact on brief tasks before working together for longer, more complex tasks, was considered an effective strategy to improve the team performance [72]. Wen et al. [111] demonstrates the advantages of participants discussions in preparation for the collaboration task. Gustavo et al.[106] introduced a mobile application to enable rapid and interactive group activities and the field study shows that team-dating interactions along with existing social ties and same gender can be a significant predictor of teammate selection. Salehi etc. constructs a field experiment of online workers from Amazon Mechanical Turk (AMT) demonstrating the value of familiarity for crowd teams and develops a tool to find the familiar team [94]. However, another field experiment in two university courses [42] showed no statistical differences between the criteria-based and randomly-assigned teams regarding the team performance.

Considering the team dynamics strategy, intermixing people by rotating team membership rather than maximizing tie strength or network efficiency can achive better team performance [93]. Sharon et al. [128] developed a system to help teams dynamically adjust the team structure to achieve better team performance. [60] shows that the collective cultural integration plays a critical role to led a successful existing team merging. Almaatouq et al. [1] proves that dynamic communication network and performance feedback provide fundamental mechanisms for both improving individual judgments and inducing the collective “wisdom of the network”.

This stream of research reveals the importance of the team formation strategy and its dynamics on the team performance. But the mix observation suggests the needs of further studies. Additionally, these studies mainly focus on the team outcome for a short-term, specific task, rather than individuals’ long-term performance. As individuals are incentivized by the long-term success in the platform, investigation of the dynamic effect of the teamwork experiences on an individual’s long term performance is necessary.

2.5 Summary

In summary, crowdsourcing is becoming a long-term career option for many crowd workers. Collaboration as an on-demand transient team is increasingly needed to solve more complex tasks. While the current research on transient teams focuses on short-term team performance based on the assumption that collaboration is beneficial and teams were already formed, collaboration as a team is not a straightforward strategy in the crowdsourcing contests. While a few studies start to investigate the teammate choice and dynamics of team structure, the strategy of working as a solo endeavor or team worker are mix for individuals, especially in the long term aspect. This unexplored and inconclusive reality motivates us to investigate whether collaboration as a transient team becomes popular, whether it is helpful for contest and individual crowd worker, and what can motivate crowd workers to work as a team in the crowdsourcing contest environment where both competition and collaboration exist simultaneously.

3 CURRENT STUDY

This study addresses four exploratory research questions to understand collaboration in crowdsourcing contests, which help crowd workers collaborate synchronously.

3.1 RQ1: Does working as a team is becoming a trend?

We start by analyzing the collaboration patterns that emerged on crowdsourcing platforms.

Given the importance of crowdsourcing platforms, how to improve the performance of crowdsourcing contests has become a hotly discussed topic [15, 20, 53, 55]. Early studies typically concerns contest-specific and individual-specific factors [15, 20, 104]. In crowdsourcing contests, participants can form transient teams of motivated individuals to compete for the rewards. With the popularity of virtual teams in crowdsourcing contests, there is an increasing interest in understanding teams' performance [36, 53, 55].

However, we know little about the trend of working as a transient team, which is a fundamental issue of studies that consider teams and their performance in crowdsourcing. Prior studies examining the collaboration patterns on crowdsourcing platforms have reported mixed results. Some of them suggest that only few individuals choose to collaborate on the crowdsourcing platform [70, 83, 102, 124]. To fill the gap, we aim to empirically capture how the proportion of working as a transient team changes over time.

Taking a step further, another exciting aspect to explore is how the design of contests affects the proportion of teams in contests. Contests on Kaggle vary in their design. For example, they varied in contest length from several days to nearly one year; they offer data with different sizes and different amounts of medals. Differences in contests design would shift the trade-off between cooperation and competition [103], demonstrated as different teamwork decisions. Following previous studies about the impact of contest designs on team performance [5, 17, 36, 120], we focus on two types of design characteristics: *complexity* characteristics and *incentive* characteristics. On the one hand, we expect that as the contest becomes more complex (e.g. shorter contest time, larger data size), there would be more teams because of the more significant advantages of collaborating. On the other hand, as extrinsic incentives increase (e.g. number of the reward), there would be fewer teams because the solo participant has more chance to be a prize winner. We aim to evaluate the effects of the two designs on the proportion of teams in contests.

3.2 RQ2: Is working as a team always a better choice?

We now move on to the second research question to understand the benefits and losses of working as a team in crowdsourcing contests.

Improving collaboration outcomes of crowdsourcing contests is a hot topic in crowdsourcing literature [24, 39, 53, 102]. However, all these studies have been conducted at the team level, which only concerns team performance outcomes. In this study, we aim to understand both team and individual performance instead of team performance only. Specifically, we focus on the performance gap between working as a transient team and individually.

In addition, team performance is usually theorized as static in previous studies. Such a static view point may be not enough as more recent studies have highlighted the longer-term orientation for these crowd workers working on more professional tasks [12, 27, 85]. To better understand the collaboration patterns of these long-term-oriented professional crowd workers, we investigate the performance gap between working as a transient team and individually from both static and dynamic perspectives. We will answer the following questions: whether working as a team is always a better choice? If not, under what condition it can be?

3.3 RQ3: How do the cumulative teamwork experiences affect individual's short-term and long-term performance?

Next, we examine whether participants with different degrees of teamwork experience have different performances in crowdsourcing contests.

To the best of our knowledge, no prior studies have taken a long-term perspective and considered the cumulative teamwork experience and its outcomes in crowdsourcing. The extant literature has focused extensively on the effects of instant factors in contests [5, 17, 36, 120], individuals [2, 24, 32, 55, 66, 76, 88], teams [24, 35, 44] and environments [16, 24, 102] on team outcome in a specific contest. In another word, all of them examine the effects of these instant factors on short-term outcomes rather than long-term outcomes.

To fill the gap, we investigate how cumulative teamwork experiences related to individuals' short-term and long-term performance. We expect that individuals in virtual teams can benefit from collaboration in the short term by gaining valuable information, obtaining support from others, and exchanging ideas, and in the long term by learning from others's expertise and from the co-creation process that happens when individuals work together.

3.4 RQ4: What factors motive participants to work as a team?

We now move on to the last research question to understand the factors that motive participants to joint teams.

Participants can obtain *intellectual capital (IC)* through competing with each other in contests. Intellectual capital refers to individuals' task-related skills and knowledge gained from experience, learning, and education [63]. Intellectual capital is known to influence the participants' actions in the context of crowdsourcing [15, 24]. In this regard, we focus on the impacts of individuals' intellectual capital on their decisions of working as a team.

Most previous studies mainly focus on the relationships between intellectual capital and team performance [24, 53, 119]. The role of intellectual capital in participants' decision-making is under investigated in the crowdsourcing literature. To further explore this question, we distinguish two types of intellectual capital in terms of different collaboration forms: solo-related intellectual capital and teamwork-related intellectual capital. The former refers to intellectual capital obtained from participants' past solo experience in contests, and the latter refers to intellectual capital obtained from participants' past teamwork experience in contests.

Intellectual capital gained from different collaboration forms (i.e., working as a team or working solely) reflects participants ability to work in teams to some extent [24]. Compared to solo-related intellectual capital, participants with higher team-related intellectual capital tend to work better with one another. Therefore, we expect a negative association between the level of solo-related intellectual capital and the likelihood of the participant deciding to work as a team. On the contrary, we expect a positive association between the level of teamwork-related intellectual capital and the likelihood of the participant deciding to work as a team.

It is also important to note that when the effect of intellectual capital on collaboration decision is most influential, previous studies have applied social capital theory to understand team behavior in different contexts [24, 53, 57, 89]. Therefore, in addition to the main effects posed above, we hypothesize about moderators that reflect structural position of participants within a collaboration network. Here, the structural position captures participants' past collaboration ties with members within a team. If participants have both high past collaboration ties and high team-related intellectual capital, they likely got a good experience from collaboration and are more likely to join teams in the future. Instead, if participants have high past collaboration ties but high sole-related intellectual capital, they probably had an awful collaboration experience and are more likely to work solely. Therefore, we hypothesize that the influence of intellectual capital becomes more vital as the intensity of past collaboration ties increases.

4 BACKGROUND AND DATA

4.1 The Kaggle Platform

In this study, we obtain data from a specialized crowdsourcing platform focusing on data analytics projects: Kaggle.com. Companies, governments, and researchers provide data sets to Kaggle along with their problems and the amount of reward they are willing to pay the winners.

Kaggle is the prominent crowdsourcing contest platform. It has been considered as the *de facto* blueprint for many other crowdsourcing contest platforms, such as DrivenData, CrowdANALYTIX, Datascience.net, TianChi and DataFountain etc., where similar features (e.g. Kernel System, Team System and Progression System discussed below) are provided. Therefore, the findings from Kaggle can be applied to these crowdsourcing contest platforms. Using the dataset from Kaggle, studies have been developed to investigate teamwork and collaboration in the crowdsourcing context, including the team discussion and solution-sharing behavior [53], salience bias [67], code sharing mechanism [102], team's social intellectual capital [24] etc.

Importantly, on Kaggle, data analysis is not trivial but a more skillful task that needs a significant amount of effort to accomplish. Each user can participate alone or team up with other members to join a contest. The team is transient, and for each contest, users need to reform a new team even if they have the same team members. This provides a perfect opportunity to investigate skilled crowd workers' decisions on forming a transient team or not.

4.1.1 Kernel System. For each contest, Kaggle provides 'Kernels' that allow users to run code directly on Kaggle. Kaggle Kernel contains the most common data science libraries and languages and the data required for analysis so that users can start the tasks more manageable. It also offers transparency of shared code, makes the entire model reproducible, and enables the user to invite collaborators when needed. Some contests will require all teams to submit their solution through Kaggle Kernel so that the submissions can be more reproducible and evaluated.

4.1.2 Team System. Everyone who joins a Kaggle contest will do as a team, while a team can be a group of one or more users who collaborate on the contest. Once a user accepts the rules and joins a contest, a new team consisting solely of the user will be created. Users can then adjust team members by inviting other users to join or accepting other users' requests to form a multi-member team. As this study focuses on the teaming-up choice, we consider a team as *"solo"* if a team only has one member, otherwise as *"team"* where it includes at least two members.

Note that not all teams who join a competition will submit solutions for evaluation, and only the teams with at least one submission during the competition will be included for performance evaluation. Additionally, members within a team do not necessarily already know each other when forming a team. One such example is described by a user as follow[2]:

"I noticed that there were several active experts, who wrote on the forum and created kernels, so I read everything from them. And one day I received an e-mail from Boris, who was an expert in this domain and thought that our skills could complement each other[...]We were lucky to also team up with Philip Margolis[...]And after little time his models showed much better results than ours[...] Another member of our team became Bojan and we were able to improve our result even further[...]Some debates ensured

[2]Reading this post for more details about this team's experiences on the Kaggle contest: https://towardsdatascience.com/a-story-of-my-first-gold-medal-in-one-kaggle-competition-things-done-and-lessons-learned-c269d9c233d1

and as a result we asked Christof to join our team. It was amazing to see how he was able to build a new neural nets extremely fast."

4.1.3 Progression System. Kaggle's Progression System uses performance tiers to track individuals' growth as a data scientist on Kaggle. Individuals earn medals for their achievements in four Kaggle categories: Competitions, Notebooks, Datasets, and Discussion. For each category, advancement through performance tiers is done independently. As this study focuses on the contest context, we will only consider the competition category [3].

During a contest, the submissions will be evaluated based on a sample set of data, ranked based on their performance, and displayed publicly in real-time. Kaggle allows teams to submit multiple solutions during a contest, and the number of submissions represents a team's productivity, which can be an indicator for a team's performance [24].

After the contest reaches its deadline, one final submission from each team will be evaluated using the full set of testing data. Each team will then be assigned a rank according to the testing score. Using this rank (*Rank*), together with the number of members on the team ($N_{\text{teammates}}$), and the number of teams in the competition (N_{teams}), each team member in the same team will be allotted a point using the following formula, , representing how well they did in the contest [24, 67, 102]:

$$\left[\frac{100000}{\sqrt{N_{\text{teammates}}}}\right]\left[\text{Rank}^{-0.75}\right]\left[\log_{10}(1+\log_{10}(N_{\text{teams}}))\right] \tag{1}$$

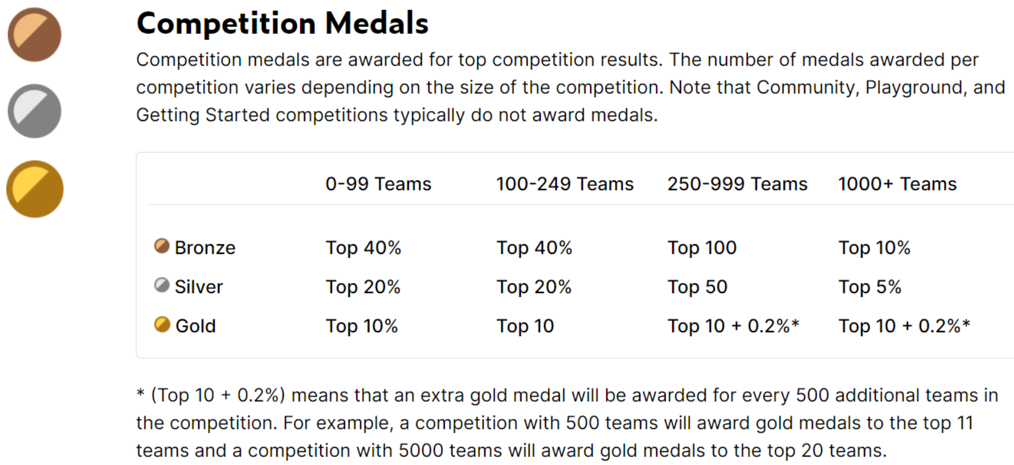
Therefore, the point allocation mechanism penalizes individuals who compete on teams with more teammates and rewards individuals with higher rankings when more total teams are competing. For site-wide ranking, Kaggle applies a decay function $e^{-t/500}$ so that points in more recent contests count for more. As we focus on the contest level performance to represent the intelligent capital, similar to [102], when calculating the cumulative number of points each participate had earned at the beginning of each context, we used the above Kaggle's formula but without applying the decay function.

Additionally, as shown in Figure 2, competition medals are awarded for top competition results, which consider both individual's ranking and the competitive intensity within a contest. For example, a contest with 500 teams will award Gold medals to the top 11 teams, Silver medals to the top 50 teams, and Bronze to the top 100 teams. The rest of the teams will not receive any medals. Hence, the medals system is a way of recognizing and rewarding the top excellent teams. To make a medal comparable among contests and teams, in this study, we assign 1 for the Gold medal, 1/2 for the Silver medal and 1/3 for the Bronze medal, respectively.

4.2 Data Collection and Overview

Our main data source is the December-13-2021 version of Meta Kaggle[4], a publicly available database provided by Kaggle. It contains data of 4,848 contests which has ended and the leaderboard has been finalized by then. The raw data also includes 4,749,060 created teams, 8,514,706 users, and 9,891,160 submission records, representing the public activity in the Kaggle platform. As Meta Kaggle does not provide the information of the dataset used for each contest, which represents one aspect of the complexity of a contest [102], we further crawled this information from the Kaggle website.

[3]We acknowledge that other category achievements can also be an indicator for individual performance and future investigations on how the different categories of performance tiers impact each other could be interesting.
[4]https://www.kaggle.com/kaggle/meta-kaggle/discussion/59870


Competition Medals

Competition medals are awarded for top competition results. The number of medals awarded per competition varies depending on the size of the competition. Note that Community, Playground, and Getting Started competitions typically do not award medals.

	0-99 Teams	100-249 Teams	250-999 Teams	1000+ Teams
Bronze	Top 40%	Top 40%	Top 100	Top 10%
Silver	Top 20%	Top 20%	Top 50	Top 5%
Gold	Top 10%	Top 10	Top 10 + 0.2%*	Top 10 + 0.2%*

* (Top 10 + 0.2%) means that an extra gold medal will be awarded for every 500 additional teams in the competition. For example, a competition with 500 teams will award gold medals to the top 11 teams and a competition with 5000 teams will award gold medals to the top 20 teams.

Fig. 2. The Kaggle's Competition Medals

4.2.1 Preprocessing and Filtering. Starting from this raw data, we filtered out the contests without submissions and teams, resulting in 3,989 contests. For teams who join these contests, we filtered out those teams without any submissions (i.e., these teams accepted the contest rules to join but did not actively participate), without a team leader (i.e., these teams do not have an assigned leader as they may be merged into other teams), or acting as a benchmark (i.e., some contests will provide benchmark solutions, which are submitted by a benchmark team). This leave us a data containing 3,989 contests, 740,710 teams, 408,400 users with 9,628,634 submissions. Note that we further filter out some data based on this dataset to meet the analysis requirement for the four research questions within this study.

4.2.2 Competition Similarity Calculation. We applied the Sentence-BERT[5] framework to compute the text embeddings of the short description for each competition. Sentence-BERT (SBERT) [91] is a modification of the pre-trained BERT network that uses siamese and triplet network structures to derive semantically meaningful sentence embeddings that can be compared using cosine-similarity. It reduces the effort for finding the most similar pair from 65 hours with BERT / RoBERTa to about 5 seconds with SBERT, while maintaining the accuracy from BERT. Then the cosine-similarity is adopted to calculate the similarity between two competitions. We acknowledge that there may be a more advanced text embedding framework emerging daily. Additionally, we only consider the short text description for each contest in this study, while using more information such as the semantic information of each dataset and the detailed contest description etc. may improve the accuracy of the similarity score. But, the current method for this study already provides a reasonably good enough competition similarity calculation. As shown in Figure 3, where the number with each line is the similarity between two contests, We can see that the featured competition pairs with a top 10 similarity are either the same competition but held in different times, or different parts of the same challenge.

[5]https://www.sbert.net/

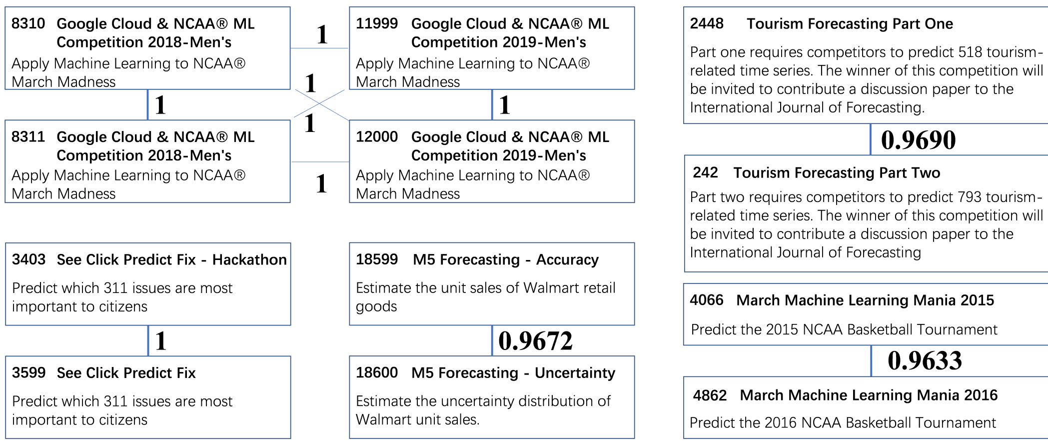


Fig. 3. The Kaggle's Featured Competition Pairs with Top 10 Similarity. The number with each line is the similarity score between two contest descriptions shown in boxes.

5 RESULT

5.1 RQ1: Does working as a team is becoming a trend?

To capture the trend of working as a team over time, we focus on *Team Ratio*, which refers to the percentage of teams with more than one member in the total number of teams (including the solo team). The higher the percentage is, the more the participants work as a team.

Based on the data we collected, we exclude those contests, which are larger than one year, and get 3,835 contests. Then, we exclude contests designated as *"recruitment"*, *"playgroup"*, or *"getting started"*, which lefts 3,724 contests. Among the 3,734 remaining contests, 599 from November 2010 to November 2021 have more than ten teams with more than one members[6], and thus these contests are included in our subsequent analyses. Table 1 summarizes the dataset we used for RQ1.

Variables (Unit)	Mean	Median	Min	Max
Team Ratio	0.387	0.262	0.033	1
Contest Length (Day)	54.25	0 50	1	314
Max Similarity	0.945	0.944	0.871	1
Data Size (GB)	1.127	0.013	0	91.435
Reward Size	64.84	0	0	873
Years After 2010 (Year)	9.172	10	1	12
Kernel Submission	True 9.18%			

Table 1. Descriptive Statistics of Data Used in RQ1 and RQ2

First, we plot the yearly average proportion of working as teams in each contest (Figure 4). As we can see, between 2010 and 2021, there is a growth in terms of the average proportion of teams in contests. That is, it seems working as a team is becoming a trend. In 2021, teams made up 50% of the total participants in each contest on average. This indicates that teams increasingly become key participants in crowdsourcing contests. Interestingly, the average proportion of teams saw a big

[6]In this study, we set this threshold to only consider those contests where collaboration as a multi-member team can be a reasonable choice.

jump in 2015. One possible explanation for this phenomenon is that Kaggle released a new feature called kernels (originally called scripts) in 2015. This shock pulls in many more users collaborating as a multi-member team of that year.

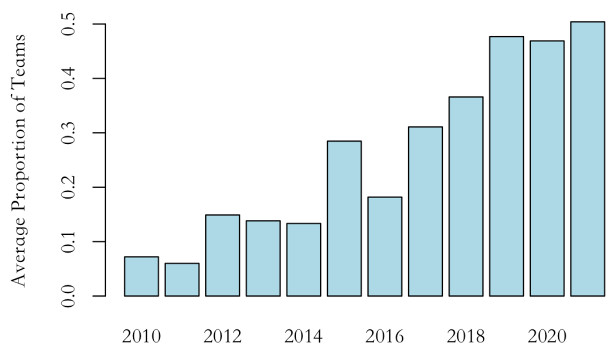


Fig. 4. Average Team Ratio Over Years

To empirically demonstrate this finding, we carry out a one-way analysis of variance (ANOVA) to ascertain whether there is statistically significant between-years difference in average proportion of teams. The results obtained in Table 2 show that there is a significant degree of between-years differentiation in the average proportion of teams in contests ($F(1, 11) = 9.907, p < 0.001$).

	Sum of Square	Degree of Freedom	F value	P value
Intercept	0.016	1	0.191	0.662
year	9.907	11	11.069	$<0.01^{***}$
Residuals	47.764	587		

Table 2. ANOVA Result for Between-years Differentiation of Team Ratio. $*: p < 0.05, **: p < 0.01, ***: p < 0.001$.

Hence, we build a linear regression model to test the associations between the proportion of teams and design characteristics of contests. The dependent variable (DV) is *Team Ratio*. As mentioned in Section 3.1, we regard complexity and incentive characteristics as key contest designs in this study. Task complexity can be operationalized in terms of its component, coordinative, and dynamic dimensions [114].

First, component complexity refers to the number of distinct information cues that must be processed in a task [114]. Since a "denser" data increases the number of information cues that must be perceived and processed, data density is often used as an indicator of component complexity of software tasks [6]. In our study, data density is measured by the bytes of data that had to analyzed (i.e., *Data Size*). That is, component complexity is higher in contests with higher levels of *Data Size*. Beside, we also use *Max Similarity*, the maximum of similarities between the focal contest and every other previous contest, to enrich the measurement of component complexity. Intuitively, a higher level of *Max Similarity* decreases the distinct information cues of a contest and its component complexity.

Second, coordinative complexity describes the complexity caused by the task coordination [114]. We use *Kernel Submission*, a dummy indicates whether the contest is a kernel only competition or not, to describe coordinative complexity of contests. That is because Kaggle kernel is more salient a factor for coordination on crowdsourcing contest platforms with which code and data are naturally reproducible, very simple to learn and extremely easy to share [102]. That means, contests that supported kernels decrease the coordinative complexity.

Third, dynamic complexity arises from changes in the relationships between information cues over time [114]. Banker et al. (1998) [6] indicates that dynamic complexity in software task is higher when there is increased instability of the input-output information cues for a task. Accordingly, we use *Contest Length*, the number of days that a contest is open and accepting submissions, to measure the instability of information cues exchange in a contest. As we can see, given the total amount of information cues that should be processed in a contest, a longer contest duration can reduce average information volatility, resulting into a lower complexity for contest participations.

For the incentive characteristic, we use one measure to capture the incentives of a contest (*Number of Reward*). We also control for the time trend (*Years After 2020*). All variables are summarized as follow:

- *Data Size*: The number of bytes of data that had to analyzed. The higher the data volume, the more complex the contest.
- *Max Similarity*: The maximum of similarities between the focal contest and every other previous contest. The more similar to previous contest, the less complex the contest.
- *Kernel Submission*: A dummy indicates whether the contest is a kernel only competition or not. Contests with kernel features are less complex.
- *Contest Length*: The number of days given to submit a solution. The longer the length, the less complex the contest.
- *Reward Size*: The total number of medals offered to participants. Contests that award more medals to the participants have higher level of extrinsic incentives.
- *Years After 2020*: The time that has passed since 2010.

As shown in Table 3, we find that the complexity-related design of contests plays an essential role in affecting teaming-up strategy. First, the longer the contest length is, the fewer participants are willing to work as teams ($Coef = -0.041, SE = 0.013, p < 0.01$). Second, as the size of the data increases, there would be more teaming behaviors ($Coef = 0.004, SE = 0.002, p < 0.05$). Third, contests in which participants can only submit results by creating kernels are associated with a smaller percentage of teams with at least two members ($Coef = -0.132, SE = 0.035, p < 0.001$). These observations are consistent with the conjecture that a more complex contest is correlated with a higher proportion of teams in the contest. This pattern may exist because an increasing level of complexity leads to increasing levels of challenge and activation [126],requiring a variety of sophisticated skills. In this regard, to increase performance and the chances of winning, working as a team will probably be chosen for its benefits, including bringing together individuals with complementary skills [48] and attracting the best individuals [75].

Additionally, we find a significant negative relationship between the number of medal and the proportion of teams during contests. The more the number of medal is, the small a participant's fraction of working as a team is ($Coef = -0.066, SE = 0.006, p < 0.001$). The significant coefficient for the *Reward Size* supports the hypothesis in Section 3.1 that extrinsic incentives have negative impacts on the proportion of working as a team. When external incentives are present, individuals rationally evaluate the outcomes of their behavior and then adjust their strategies to attain the incentives [22]. From this perspective, given more medals, individuals may see less benefit to working as a team, resulting in fewer teaming behaviors. Table 3 also verifies the increasing trend of working as a team when participating in contests. The proportion of teams increases as time goes by ($Coef = 0.021, SE = 0.005, p < 0.001$).

DV: *TeamRatio*	Coef.	SE
Intercept	-0.068	0.463
Contest Length	-0.041**	0.013
Max Similarity	0.711	0.705
Data Size	0.004*	0.002
Kernel Submission	-0.132***	0.035
Reward Size	-0.066***	0.006
Years After 2010	0.021***	0.005
Adj. R^2	0.537	

Table 3. Regression Results for the Evolution of Team Ratio. SE is the abbreviation for standard error. $* : p < 0.05, ** : p < 0.01, *** : p < 0.001$.

5.2 RQ2: Is working as a team always a better choice? If not, under what conditions is?

We investigate whether working as a team is always a better choice. We first approach this research question from a static point of view. That is, we start off by investigating the gap in overall performance between team and solo. We consider the following three metrics to capture the performance gap between working as a team and working solely on Kaggle:

- ***Average Medal Gap***: The gap in average amount of medals between team and solo.
- ***Average Point Gap***: The gap in average amount of points between team and solo.
- ***Average Productivity Gap***: The gap in average amount of submissions between team and solo.

Based on the data containing 599 contests, we calculate the mean of these three metrics and their 95% confidence interval correspondingly (Table 4). It is observed that the mean of *Average Medal Gap* and *Average Productivity Gap* are larger than zero, and all 95% confidence intervals do not include zero. That is, compared to working individually, working with teams is correlated with better performances in terms of the number of medals and submissions. This indicates that working as a team can improve productivity during the contests and have a higher chance to get better medals. Note that Kaggle rewards medals in team bias which means that every team member will achieve the same. In other words, working as a team will help the team members to have a better performance regarding medal achievement.

Instead, the mean of *Average Point Gap* is less than zero, and 95% confidence intervals do not include zero. That means, compared to working individually, working with teams is correlated with worse performances in terms of the number of points. This indicates that the design of the point systems in Kaggle may penalize teamwork too much to discourage individuals to work as a team.

Performance Measure	Mean	95% Confidence Interval
Average Medal Gap	0.050	(0.044,0.057)
Average Point Gap	-1631657	(-1832108,-1431205)
Average Productivity Gap	15.047	(13.880,16.215)

Table 4. Average Gaps in Performance and Their Confidence Intervals

Next, we approach this research question from a dynamic point of view. We are interested in investigating how the performance gaps evolve over time. First, a one-way ANOVA is adopted to test whether there is a statistically significant between-years difference in average performance gaps. Table 5 shows that *Average Medal Gap* ($F(1, 11) = 10.096, p < 0.001$), *Average Point Gap*

($F(1, 11) = 3.625, p < 0.001$), and *Average Productivity Gap* ($F(1, 11) = 1.623, p = 0.088$) have significant degree of between-years differentiation. These results highlight the importance of a dynamic perspective.

	Sum of Square	Degree of Freedom	F value	P value
Average Medal Gap				
Intercept	0.154	1	28.722	1.202e-07 ***
year	0.595	11	10.096	$< 0.001^{***}$
Residuals	3.147	587		
Average Point Gap				
Intercept	2.710	1	149.604	$<0.001^{***}$
year	0.724	11	3.625	$<0.001^{***}$
Residuals	10.632	587		
Average Productivity Gap				
Intercept	157	1	0.749	0.387
year	3751	11	1.623	0.088.
Residuals	123299	587		

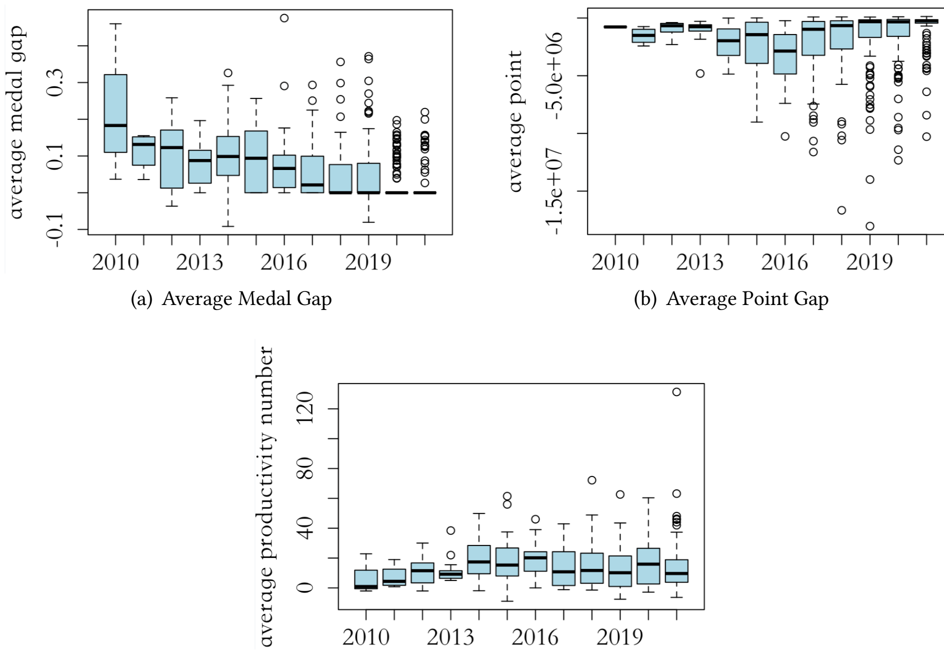
Table 5. ANOVA Results. $* : p < 0.05, ** : p < 0.01, *** : p < 0.001$.

We plot yearly distributions of the three metrics to capture the dynamic trends (See Figure 5a-c). As for the benefits of working as a team, the benefits on average amount of medals decrease between 2010 and 2021 (See Figure 5a). On the contrary, the benefits on average amount of submission sees a increase from 2010 to 2021 (See Figure 5c). As for the loss of points for working as a team, there seems to be no significant linear trend over time (See Figure 5b).

To empirically examine the time trend of performance gaps between team and solo, we build three linear regression models where the dependent variables are the *Average Medal Gap*, *Average Point Gap*, and *Average Productivity Gap*, respectively, while the independent variable is the time that has passed since 2010 (i.e., *Years After 2010*). We also control for the contest characteristics related to complexity mentioned in RQ1, including *Contest Length*, *Max Similarity*, *Data Size*, and *Only Allow Kernel Submission*.

Result shown in Table 6 suggests a statistically significant negative correlation between the time and the gap in average amount of medals awarded($Coef = -0.010, SE = 0.001, p < 0.001$). With respect to the gap in average amount of submissions, however, we find it to be significantly positively correlated to the time ($Coef = 0.753, SE = 0.226, p < 0.01$). Similar to the pattern in Figure 5b, there is no clear relationship between the time and the gap in average points gained.

These observations conclude that the benefit of working as a transient team varies. From a static perspective, working as a transient team is correlated with better performances in terms of medals and submissions but worse performances in terms of points. Teamworks can be more productive, demonstrated as more submissions, and develop higher-quality solutions demonstrated as the achieved medals. However, the penalty on teamwork from Kaggle's point systems design overturns the benefits from teamwork. From a dynamic perspective, the benefits of the average amount of medals decrease over time while the average amount of submissions increases over time. This means that as time goes by, the teamwork can still be productive, but the surplus of teamwork in submission quality is dismissed. This is an interesting finding. Tausczik and Wang [102] found that during a contest, while users collaborate on Kaggle through code sharing, there is lack of top-performance code sharing. Hence, our study confirm such a long-term trend in Kaggle. In



(a) Average Medal Gap

(b) Average Point Gap

(c) Average Productivity Gap

Fig. 5. The Trend of Performance Gaps

	Medal Gap		Point Gap		Productivity Gap	
	Coef.	SE	Coef.	SE	Coef.	SE
Intercept 2010	0.084	0.145	0.311	0.269	16.236	29.830
Time After 2010	-0.010***	0.001	0.001	0.002	0.753**	0.266
Contest Length	0.021***	0.004	-0.046***	0.007	4.666***	0.735
Max Similarity	-0.090	0.220	1.200**	0.409	-50.5081	45.381
Data Size	0.002***	0.001	-0.002	0.001	0.456***	0.132
Kernel Submission	0.046***	0.010	-0.108***	0.019	1.888	2.086
Adj. R^2	0.317		0.230		0.140	

Table 6. Regression Results of Performance Gap Evolution over Year. $* : p < 0.05$, $** : p < 0.01$, $*** : p < 0.001$. SE is the abbreviation for standard error.

another word, in the long-term, working as a team is increasingly helpful for solution developments but has decreasing benefit in improving solution quality.

On the other hand, we can see that the Kernal system has a significant positive effect on the medal gap and a negative effect on the point gap. This means that compared with the solo teams, team workers can adopt the Kernel system better to achieve a better submission quality improvement and remedy the penalty on teamwork brought by the Kaggle point system.

These observation reflects one common critiques of the Kernel system in Kaggle is "allowing people to achieve high leaderboard positions with very little effort"[7]. This could amplify the negative effect from social interaction by increasing the individual similarity[1, 8, 71, 80], which can reduce the benefit of working as a team. Hence efforts to further power the Kernel system to support team collaboration for higher quality, rather than just mediocre, solutions development are needed for the platform.

5.3 RQ3: How do the cumulative teamwork experiences affect individuals' short-term and long-term performance?

We investigate the effects of collaboration experiences on individuals' short-term and long-term performance. Starting from the data containing 3,989 contests and 408,400 users, we only consider the users who participate at least 30 contests since 2010 so that we can observe the long-term behaviors of users in the platform, leaving us 1006 users in the dataset. We further filter out users who constantly work at a team (in other words, never work solely) and users who never work with a team (in other words, always work solely), which lefts participant-level panel data for 666 participants involving 979 contests from April 2010 to December 2021[8]. Table 7 summarizes the data we used in subsequent analyses.

Variables (Unit)	Mean	Median	Min	Max
Contest Length (Day)	85.82	84	0	1341
Max Similarity	0.935	0.933	0.862	1.000
Data Size (GB)	2.079	0.060	0.000	91.435
Time After 2010 (Year)	8.623	9	1	12
User Tenure (Day)	1107	983	0	4161
log(Cumulative Collaboration)	17.65	18.44	0.00	20.91
log(Weighted Team-related IC)	15.09	15.30	0.00	18.50
log(Weighted Solo-related IC)	17.48	18.34	0.00	20.91
Prior Collaboration Ties	11.88	3	0	192
log(Cumulative Points)	17.65	18.44	0	20.91
Cumulative Medals	5.263	2.333	0	85.667
log(Points)	14.21	15.05	0.00	17.95
Choice	Work as a team 18.10%			
Medals	Gold 4.95%, Silver 12.79%, Bronze 10.81%, None 71.45%			
Kernel Submission	True 23.11%			

Table 7. Descriptive Statistics of Data Used in RQ3 and RQ4

Several regression models where dependent variables are the individuals' short-term and long-term performance respectively, and individuals' total cumulative proportion of working as a team ($CumulativeCollaboration_{i,t}$) is used as independent variables. We use two dependent variables to capture an individual's short-term performance (i.e., $Points_{i,t}$ and $Medals_{i,t}$) and two dependent variables to capture an individual's long-term performance (i.e., $CumulativePoints_{i,t}$ and $CumulativeMedal_{i,t}$).

- $Points_{i,t}$: The number of points individual i earned for his/her performance in a contest t using the Kaggle Point formula in Equation 1, which is a continuous variable.

[7] https://www.kaggle.com/code/dvasyukova/scripty-mcscriptface-the-lazy-kaggler/notebook
[8] While only considering users with at least 30 contests filtering out many users, it enables us to study the sustained participated users and observe the long-term effect in the platforms, which is the goal of this study.

- $Medal_{i,t}$: The medal individual i awarded for his/her performance in a contest t, which is a ordinal variable with four values (gold, silver, bronze medal, and none).
- $CumulativePoints_{i,t}$: The cumulative number of points[9] an individual i had gained on the platform at the beginning of a contest t.
- $CumulativeMedals_{i,t}$: The cumulative number of medals an individual i had been awarded on the platform at the beginning of a contest t.

We also include a random effect for the user ID and control for complexity-related contest characteristics (i.e., $ContestLength_{i,t}$,$DataSize_{i,t}$,$MaxSimilarity_{i,t}$, and $KernelSubmission_{i,t}$). It is noting that we adopt a ordered probit model for the ordinal $Medal_{i,t}$ variable.

Table 8 shows that a higher degree of cumulative collaboration experience is associated with doing better in gaining points ($Coef = 0.847, SE = 0.177, p < 0.001$) and medals ($Coef = 1.590, SE = 0.044, p < 0.001$) after controlling for contest characteristics. Furthermore, Table 9 indicates that individual's cumulative collaboration experience is associated with higher long-term performance in terms of cumulative points ($Coef = 3.050, SE = 0.159, p < 0.001$) and cumulative medals ($Coef = 1.609, SE = 0.024, p < 0.001$) even after controlling for user tenure and time. Both of these results suggest that collaboration experience is associated with better individual short-term performance in a contest and long-term performance over many contests.

This finding contrasts with prior works on the effects of instant factors on team short-term outcome (e.g., [36, 44, 55]). In contrast with such works, our findings more clearly support both short-term and long-term benefits of cumulative-oriented factors (i.e., cumulative teamwork experiences). These results are likely due to the benefits of past teamwork experience. Previous studies on teamwork indicates that by teaming up individuals can evolve and grow their knowledge and expertise rapidly [25]. Moreover, teamwork can expand individuals' perspectives of problems [79]. Thus, individuals' previous cumulative teamwork experiences will improve their performance in the contests.

	Points		Medals	
	Coef.	SE	Coef.	SE
Intercept	16.314***	0.817		
Cumulative Collaboration	0.847***	0.177	1.590***	0.044
Max Similarity	-5.263***	1.211	-1.535**	0.555
Contest Length	0.257***	0.030	0.108***	0.015
Data Size	0.012***	0.004	0.009***	0.002
Kernel Submission	0.218***	0.039	-0.216***	0.017
Threshold (None-Bronze)			0.361	0.374
Threshold (Bronze-Silver)			0.737*	0.374
Threshold (Silver-Gold)			1.494***	0.374
Individual FE	-Included-		-Included-	
Num obs.	35,631		35,631	

Table 8. Individual Short-Term Performance. $*: p < 0.05, **: p < 0.01, ***: p < 0.001$. SE is the abbreviation for standard error.

[9]Note that we do not apply the decay function following [102].

	Cumulative Points		Cumulative Medals	
	Coef.	SE	Coef.	SE
Intercept	1.588***	0.152	-3.101***	0.033
Cumulative Collaboration	3.050***	0.159	1.609***	0.024
User Tenure	2.146***	0.030	0.3535***	0.005
Time After 2010	0.134***	0.013	0.190***	0.002
Individual FE	Included		Included	
Num obs.	35,631		35,631	

Table 9. Individual Long-Term Performance. $*: p < 0.05, **: p < 0.01, ***: p < 0.001$. SE is the abbreviation for standard error.

5.4 RQ4: What factors motive participants to work as a team?

First, we empirically examine how the solo-related and team-related intellectual capital of the participant affects his/her choice of working as a team.

Based on the dataset used in RQ3, we build a discrete choice model to test the association between participants' intellectual capital and their collaboration decision. The dependent variable is $Choice_{i,t}$, which is a dummy variable that indicates a participant's decision on working as a team. $Choice_{i,t}$ equals 1 if participant i has joined a team with multiple members in a contest t, and 0 otherwise. We distinguish two different individual's intellectual capitals: the weighted solo-related intellectual capital and the weighted team-related intellectual capital to capture a participant's intellectual capital from previous teamwork or sole-work. They are measured as follow, which are the independent variables in this study.

- *Weighted Solo-related* $IC_{i,t}$: For each historical contest k participant i had *participate as a solo worker* before contest t, We first calculate the points i had earned from contest k using the Kaggle point formula, and then use the similarity[10] between the focal contest t and contest k to weight the point participant i gain from contest k. Finally, we calculate the cumulative number of these weighted points participant i had earned before the beginning of each contest t.
- *Weighted Team-related* $IC_{i,t}$: Similarly, for each historical contest q participant i had *participate as a team worker* before contest t, We first calculate the points i had earned from contest q using the Kaggle point formula, and then use the similarity between the focal contest t and contest q to weight the point participant i gain from contest q. Finally, we calculate the cumulative number of these weighted points participant i had earned before the beginning of each contest t.

Additionally, any registered users can participate in the competitions. The user tenure refers to the amount of days since users had joined the community. Previous studies have shown that the team average tenure can be positively related to team performance [24]. Hence user tenure can be an indicator about an individual's experience on the Kaggle platform, and a senior user is expected to achieve a better performance for a contest.

Table 10 summarizes the results of the first-stage analysis. In the main effect model, the solo-related intellectual capital shows the negative and significant influence on the participants' likelihood of joining a team ($Coef = -0.115, SE = 0.005, p < 0.001$). In contrast, the team-related

[10]Note that we also apply the version without consider the contest similarly and the result is robust, except a relative lower log-likelihood.

intellectual capital shows a positive and significant influence on the participants' likelihood of joining a team ($Coef = 0.187, SE = 0.007, p < 0.001$). The probable reason may be the path dependency effect [26]: Once a past decision has become sufficiently informative, individuals will simply copy the past decision because of its superior performance or lower costs. In our case, as the individual build up more solo-related intellectual capital, he or she becomes more proficient at performing established routines and practices [90], which reduces his or her cost of being a solo endeavor in the future and enhances the tendency to working individually. On the other hand, a higher level of team-related intellectual capital indicates the remarkable ability of individuals to coordinate their activity [90], in which case working as a team is cost-effective. Moreover, a team's intellectual capital can positively influences team performance [24], which proves the superiority of working as a team. Therefore, individuals with higher level of teamwork-related intellectual capital will persist in working as a team.

	Main Effect		Moderating Effect	
DV: $Choice_{i,t}$	Coef.	SE	Coef.	SE
Intercept	-1.666**	0.533	-1.079	0.602
Weighted Solo-related IC	-0.115***	0.005	-0.013	0.010
Weighted Team-related IC	0.187***	0.007	0.017	0.016
User Tenure	-0.071***	0.017	-0.179***	0.018
Max Similarity	-0.318	0.776	-0.063	0.790
Time After 2010	-0.004	0.006	-0.006	0.006
Duration	0.091***	0.020	0.100***	0.021
Data Size	0.020***	0.002	0.020***	0.002
Kernel Submissions	0.017	0.024	0.017	0.024
Prior Collaboration Ties			0.924***	0.120
Weighted Solo-related IC:Prior Collaboration Ties			-0.055***	0.005
Weighted Team-related IC:Prior Collaboration Ties			0.023***	0.006
Individual FE	-Included-		-Included-	
Num obs.	35,631		35,631	
Log-Likelihood	-11557.19		-11080.84	

Table 10. Factors to motivate teamwork in crowdsourcing contest. $* : p < 0.05, ** : p < 0.01, *** : p < 0.001$. SE is the abbreviation for standard error.

Interestingly, we can also observe a negative and significant effect from the user tenure, meaning that the longer a user participate in the platform, the lower likelihood that he/she will work as a team ($Coef = -0.071, SE = 0.017, p < 0.001$). The probable reason for this observation can be that as individual becomes more experienced in the platform, the surplus from skill complementary by teaming-up with others [64, 115] dismissed and the diversity-innovation effect is inverted [38, 45, 55, 65, 115, 118]. Hence more senior individuals in the platform intend to work solely.

We further investigated how participants' structural positions within collaboration networks affect the relationship between intellectual capital and decision of working as a team by considering the moderating effect of the former on the latter. We use $PriorCollaborationTies_{i,t}$ to measure participant's structural positions, which is calculated by the total number of collaboration ties with members within previous teams that user i participate before the contest t.

As we can see in Table 10, the interaction effect of solo-related intellectual capital and prior collaboration ties is negative and significant ($Coef = -0.055, SE = 0.005, p < 0.001$), and the interaction effect of team-related intellectual capital and prior collaboration ties is positive and significant ($Coef = 0.023, SE = 0.006, p < 0.001$). That is to say, as the intensity of prior collaboration ties increases, the negative impact of solo-related intellectual capital on participants' likelihood of joining a team becomes more negative, and the positive impact of team-related intellectual capital on participants' likelihood of joining a team become more positive. Hence, the impacts of solo-related and team-related intellectual capital on individuals' collaboration decisions become stronger as the intensity of prior collaboration ties increases. In other words, when deciding to work as a team or not in a new contest, users will follow their prior experiences.

Overall, regarding teamwork decision in the Kaggle platform, through distinguishing the teamwork-related and solo-related intellectual capital, this analysis reveals a significant path dependency effect mediated by individual's prior teamwork experience. This effect can shape the individual's choice for working as a team or solely.

6 CONCLUSION AND DISCUSSION

6.1 Answering Our Research Questions

This paper presents a data-driven empirical study on Kaggle to understand the provision of virtual teams in online crowdsourcing contest platform. We adopt a dynamic perspective to represent relationships between time and the proportion of working as a team on Kaggle. The time trend suggests a growth in the average proportion of working as a transient team.

Although working as a team is becoming a trend, it is not always a better choice. The results show that compared to working individually, working with teams is correlated with better performances in terms of the solution quality (demonstrated as the number of medals) and productivity (demonstrated as the number of submissions) but worse performances in terms of the number of points. Furthermore, the performance gaps between teams and solos evolve over time. While teamwork is becoming more productive, the advantage for gaining more medals is decreasing.

Participants' cumulative teamwork experiences has important associations with their short-term and long-term performance in contests. This confirms our expectation that individuals in a transient team can benefit from collaboration in the short term by gaining valuable information, obtaining support from others, and exchanging ideas, and in the long term by learning from others's expertise and from the co-creation process that happens when individuals work together.

Finally, participants' intellectual capital can affect their decision to work as a team. Participants who have more team-related intellectual capital tend to work as a team, and participants who have more solo-related intellectual capital tend to work individually. Importantly, participants' structural positions within collaboration networks, measured by participants' prior collaboration ties, moderate the relationship between intellectual capital and the likelihood of joining a team. As the prior collaboration tie increases, the influence of negative solo-related intellectual capital and the influence of positive team-related intellectual capital becomes stronger. This moderated path dependency effect on teamwork decision may indicate that a solo worker will become worse in working together with others so that the collaboration with others, if that happens, can be painful. This will push the solo worker to choose to continuously work solely in the future. On the contrary, a team worker will better collaborate with others, resulting in a better experience from teamwork and working as a team in further contests.

6.2 Revisiting Previous Work

The team performance is a hot-discussed topic in the crowdsourcing literature [24, 53, 82] as well as literature in other related filed (i.e., scientific activity, and knowledge production). For example, Wu et al. [115] demonstrated the benefits of working as a team and differentiated the contributions of small and large teams in the creation of scientific papers, technology patents and software products:

smaller teams tend to create new and disruptive ideas, whereas larger teams have tended to build on existing ones. Similarly, Wuchty et al. [117] explored the impact of teamwork on papers' citation rate. They found that team size has grown steadily each year and the citation advantage of teams has been increasing with time. To some extent, our study identifies several similar results: working as a team is also becoming a trend in crowdsourcing contests (see Table 3); Moreover, working as a team is correlated with better performance (see Table 4). However, our result is not in line with Wuchty et al. [117] in terms of the increasing advantage of teams. We find a significant negative correlation between the time and the gap in average amount of medals awarded.

Our study also focuses on the collaboration as an on-demand transient team. Current research on transient teams assumes collaboration is beneficial and focused on short-term team performance. As discussed before, factors that influence the short-term team performance can be separated into four categories: contest-specific factors [5, 17, 36, 120], individual-specific factors [2, 55, 88], team-specific factors [82, 92, 115, 128], and environment-specific factors [16, 24, 102]. In our study, we take both short-term and long-term performance into account. As for the short-term performance, our results are in line with previous studies which highlighted the increase of short-term team performance. As for the long-term performance, our results provide initial evidence that individuals can also benefit from collaboration in the long term.

Previous studies in network and management science have reported mixed results regarding the benefits of collaboration in individual and team-level performance. Seufert et al. [97] believed the network perspective to be crucial for managing knowledge creation and transfer within organizations and conceptualized knowledge networking, where a number of people are assembled in order to accumulate and use knowledge. Mason and Watts [77] explored the relation between network structure and collaborative learning and found that networked groups generally outperformed equal-sized collections of independent problem solvers. On the contrary, Bernstein et al. [11] focused on how the network structure of social influence affect team performance and suggested that social influence reduced exploration and thus depressed the quality of top solutions. In our study, we focus on the teaming up decision instead of team performance. Importantly, we extending the social influence theory by exploring two types of individuals' intellectual capital in terms of different collaboration forms (solo-related capital and teamwork-related capital). Our study reveals the different roles of these two capitals on their teamwork choices, which results in a path dependence effect for team formation decision.

6.3 Design Implications

Our findings have many practical implications for participants of crowdsourcing, including the long-term-oriented professional crowd workers, the contest organizers and platform operators such as Kaggle, DrivenData, CrowdANALYTIX, Datascience.net, TianChi and DataFountain etc.

For participants, as working as a transient team is correlated with better performances in medals but worse performances in points, a straight-forward lesson here is that if a participant prefers medals, it might be a better idea for him/her to compete as a team, and if a participant prefers to points, him/her had better to work individually. In addition, the cumulative teamwork experience is shown to be associated with better short-term and long-term performance. Additionally, we can observe a path dependency effect for acting as a solo or team worker. This would suggest that participants who are long-term-oriented and want to become a professional crowd worker are encouraged to do more teamwork to cumulative their teamwork experience, especially in their early stage in the platform.

From the platform operator's point of view, findings obtained in this paper provide several insights to improve the operation of the crowdsourcing platforms to cultivate the teamwork. First of all, particular emphasis should be placed on the operation of virtual teams in crowdsourcing contests.

Our results shown that there is a growth in terms of the average proportion of teams in contests. In 2020, about half of competitors in contests are teams with more than one members, which indicates that teams increasingly become key participants in crowdsourcing contests. Supporting the collaboration among teams is becoming a critical mission.

Next, our findings also offer several guidelines for contest organizers and crowdsourcing platform practitioners who want to incentivize collaboration. On the one hand, there are a few approaches contest organizers could take. They could increase the complexity of the contests, such as shorter contest length, more data size, and without requiring kernel submission only; or they could reduce the total number of medals. On the other hand, relationships between intellectual capital and teamwork choice, as revealed in our study, can potentially be used for further optimizing the points assignment algorithms used in the platform. As the results suggest, higher team-related intellectual capital facilitates teamwork, while higher sole-related intellectual capital hinders teamwork. That is, higher team-related intellectual capital and lower sole-related intellectual capital could boost collaboration. However, in practice, the formula Kaggle used to allocate points penalizes individuals who compete on teams with more teammates, hindering participants' intent to work as a team. We recommend that the crowdsourcing platforms modify their points allocation algorithms by remedying such penalties.

Additionally,the positive team-related intellectual capital and negative solo-related intellectual capital on teamwork choice are moderated by the prior collaboration experience. As demonstrated by recent studies, the team formation strategy such as team dating [106] and community discussions [111] before collaboration can be helpful to identify the right teammate and improve the teamwork experience. Hence, platforms could explore these team formation strategies to develop the right team and improve the collaboration experiences, especially for those solo endeavors. Just as elaborated by the team formation example in Section 4.1.2, *"[...]I read everything from them. And one day I received an e-mail from Boris[...]"*, facilitating the teammate identification and new connection development would be useful.

As for team performance improvement, platforms should pay more attention to the kernel feature. This study suggests that the Kernel system has a significant positive effect on the medal gap and a negative effect on the point gap. That is, the kernel feature increases the benefit of working as a team in earning medals and reduces the disadvantage of working as a team in gaining points. Actually, the kernel system on Kaggle allows participants to run code directly on Kaggle and share code publicly with others. However,the observed negative effect of Kaggle kernel on teamwork ratio (see Table 3) indicates the weakness of Kaggle Kernel for teamwork collaboration. Additionally, our study shows a decreasing trend of surplus in medal gaining for teamwork (see Table 6), indicating the amplification of the negative effect of social influence due to individual similarity increasing in Kaggle in the long term. Therefore, empowering the teamwork collaboration capability of the Kernel system, especially for high quality solution development, could be a beneficial option that Kaggle could take.

6.4 Limitation and Future Work

Our current study suffers from several limitations, which open avenues for further studies. First of all, in this work, we only conduct a case study with one particular crowdsourcing platform, Kaggle, to understand the collaboration pattern in crowdsourcing contests. Some observations reported in this study may be attributed to the specific ways that Kaggle operates and may not generalize to other platforms. For example, different platforms may adopt different formula of the point assignment, where the penalty on teamwork may not as significant as Kaggle. Given Kaggle's being the *de facto* blueprint for crowdsourcing contest platform operation such as the design of Kernel system, team system and progression system etc., this study's conclusion could be representative enough to understand the teaming-up strategies, the short-term and long-term performance patterns within crowdsourcing contest platforms using the similar designs. However, additional empirical and comparative studies could be done with data from other crowdsourcing platforms to confirm the generalization of results revealed in this study.

Another limitation is the quality of data we can obtain from Meta Kaggle. As we can see, the sample size used in our analyses is not very large. Although this data contains 8,514,706 users, our analyses exclude many records because of poor data quality, such as records without submissions and teams, records without team leaders, etc. Besides, our analyses are constrained by the publicly provided data range. For example, as shown in Tables 6, when we fit regression models to understand how time trend and contest design characteristics are associated with performance gaps between team and solo, we find the fitted models have relatively large intercepts and low R^2. The relatively poor model fits could be partly caused by the possibility that the models do not capture additional essential factors for explaining the performance gap. These factors are beyond the access of the Meta Kaggle.

In addition, this study proposes several potential explanations for our observations, which may not be correct. For example, the path dependency effect for workers to work solely or collaboratively indicates that solo endeavors may not work well with teams, resulting in a worse collaboration experience. However, we do not have direct insight into participants' mental states, motivations, or perceptions. This study would be strengthened by future work which uses surveys of participants to match participants' mental perceptions with collaboration behavior or further in-depth investigations into the interactions among team members and other users in the community. While we suggest some design implementation to promote teamworks in crowdsourcing contests, further field studies to evaluate the effectiveness of different designs could be very valuable.

Another critical future direction of this work is to move beyond the question of "how do participants collaborate in the crowdsourcing contests" to the more profound question of "why do participants collaborate in the crowdsourcing contests,", to support the long-term, synchronous team collaboration. To this end, a qualitative, interview-based study will again help.

Finally, we note that as the working style in crowdsourcing shifts from one-off, independently working to long-term, synchronous team collaboration, there is a rich amount of research opportunities emerging for better mining knowledge of how long-term-oriented professional crowd workers collaborate. Our study, in some sense, is an example of such kind of research. We hope more research will be conducted in the future to thoroughly examine the unique aspects of collaboration patterns in crowdsourcing and gain deeper knowledge of and how transient collaboration unfolds and affects an individual's long-term success.

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REFERENCES

[1] Abdullah Almaatouq, Alejandro Noriega-Campero, Abdulrahman Alotaibi, P. M. Krafft, Mehdi Moussaid, and Alex Pentland. 2020. Adaptive social networks promote the wisdom of crowds. *Proceedings of the National Academy of Sciences of the United States of America* 117, 21 (2020), 11379–11386. https://doi.org/10.1073/pnas.1917687117

[2] Jeff Alstott, Giorgio Triulzi, Bowen Yan, and Jianxi Luo. 2017. Inventors' explorations across technology domains. *Design Science* 3 (2017), 1–29. https://doi.org/10.1017/dsj.2017.21

[3] Katharine A. Anderson. 2017. Skill networks and measures of complex human capital. *Proceedings of the National Academy of Sciences of the United States of America* 114, 48 (2017), 12720–12724. https://doi.org/10.1073/pnas.1706597114

[4] Ira Anjali Anwar, Joyojeet Pal, and Julie Hui. 2021. Watched, but Moving: Platformization of Beauty Work and Its Gendered Mechanisms of Control. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW3 (2021), 1–20. https://doi.org/10.1145/3432949

[5] Nikolay Archak. 2010. Money, glory and cheap talk: Analyzing strategic behavior of contestants in simultaneous crowdsourcing contests on TopCoder.com. In *Proceedings of the 19th International Conference on World Wide Web, WWW '10*. 21–30. https://doi.org/10.1145/1772690.1772694

[6] Rajiv D Banker, Gordon B Davis, and Sandra A Slaughter. 1998. Software development practices, software complexity, and software maintenance performance: A field study. *Management science* 44, 4 (1998), 433–450.

[7] Barry L. Bayus. 2013. Crowdsourcing new product ideas over time: An analysis of the Dell IdeaStorm community. *Management Science* 59, 1 (2013), 226–244. https://doi.org/10.1287/mnsc.1120.1599

[8] Joshua Becker, Devon Brackbill, and Damon Centola. 2017. Network dynamics of social influence in the wisdom of crowds. *Proceedings of the National Academy of Sciences of the United States of America* 114, 26 (2017), E5070–E5076. https://doi.org/10.1073/pnas.1615978114

[9] Suzanne T. Bell, Anton J. Villado, Marc A. Lukasik, Larisa Belau, and Andrea L. Briggs. 2011. Getting specific about demographic diversity variable and team performance relationships: A meta-analysis. *Journal of Management* 37, 3 (2011), 709–743. https://doi.org/10.1177/0149206310365001

[10] Francesca Bellesia, Elisa Mattarelli, Fabiola Bertolotti, and Maurizio Sobrero. 2019. Platforms as entrepreneurial incubators? How online labor markets shape work identity. *Journal of Managerial Psychology* 34, 4 (2019), 246–268. https://doi.org/10.1108/JMP-06-2018-0269

[11] Ethan Bernstein, Jesse Shore, and David Lazer. 2018. How intermittent breaks in interaction improve collective intelligence. *Proceedings of the National Academy of Sciences of the United States of America* 115, 35 (2018), 8734–8739. https://doi.org/10.1073/pnas.1802407115

[12] Allie Blaising, Yasmine Kotturi, Chinmay Kulkarni, and Laura Dabbish. 2020. Making it Work, or Not : A Longitudinal Study of Career Trajectories Among Online Freelancers. *ACMHum.-Comput. Interact. 4, CSCW3* 4, December (2020), 29.

[13] Mark Boons, Daan Stam, and Harry G. Barkema. 2015. Feelings of Pride and Respect as Drivers of Ongoing Member Activity on Crowdsourcing Platforms. *Journal of Management Studies* 52, 6 (2015), 717–741. https://doi.org/10.1111/joms.12140

[14] Mark Boons, Daan Stam, and Harry G. Barkema. 2015. Feelings of Pride and Respect as Drivers of Ongoing Member Activity on Crowdsourcing Platforms. *Journal of Management Studies* 52, 6 (2015), 717–741. https://doi.org/10.1111/joms.12140

[15] Kevin J Boudreau, Nicola Lacetera, and Karim R Lakhani. 2011. Incentives and problem uncertainty in innovation contests: An empirical analysis. *Management science* 57, 5 (2011), 843–863.

[16] Kevin J. Boudreau and Karim R. Lakhani. 2015. "open" disclosure of innovations, incentives and follow-on reuse: Theory on processes of cumulative innovation and a field experiment in computational biology. *Research Policy* 44, 1 (2015), 4–19. https://doi.org/10.1016/j.respol.2014.08.001

[17] Angelika C. Bullinger, Anne Katrin Neyer, Matthias Rass, and Kathrin M. Moeslein. 2010. Community-based innovation contests: Where competition meets cooperation. *Creativity and Innovation Management* 19, 3 (2010), 290–303. https://doi.org/10.1111/j.1467-8691.2010.00565.x

[18] Hancheng Cao, Vivian Yang, Victor Chen, Yu Jin Lee, Lydia Stone, N'godjigui Junior Diarrassouba, Mark E. Whiting, and Michael S. Bernstein. 2021. My Team Will Go On: Differentiating High and Low Viability Teams through Team Interaction. In *Proceedings of the ACM on Human-Computer Interaction*, Vol. 4. 1–27. https://doi.org/10.1145/3432929 arXiv:2010.07292

[19] Prerna Chikersal, Maria Tomprou, Young Ji Kim, Anita Williams Woolley, and Laura Dabbish. 2017. Deep structures of collaboration: Physiological correlates of collective intelligence and group satisfaction. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW*. 873–888. https://doi.org/10.1145/2998181.2998250

[20] David J Cooper and John H Kagel. 2005. Are two heads better than one? Team versus individual play in signaling games. *American Economic Review* 95, 3 (2005), 477–509.

[21] Juan Carlos Alvarez De La Vega, Marta E. Cecchinato, and John Rooksby. 2021. Why lose control? a study of freelancers' experiences with gig economy platforms. *Conference on Human Factors in Computing Systems - Proceedings* (2021), 1–25. https://doi.org/10.1145/3411764.3445305

[22] Edward L Deci and Richard M Ryan. 2000. The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological inquiry* 11, 4 (2000), 227–268.

[23] Paul M. Di Gangi and Molly Wasko. 2009. Steal my idea! Organizational adoption of user innovations from a user innovation community: A case study of Dell IdeaStorm. *Decision Support Systems* 48, 1 (2009), 303–312. https://doi.org/10.1016/j.dss.2009.04.004

[24] Indika Dissanayake, Jie Zhang, and Bin Gu. 2015. Task division for team success in crowdsourcing contests: Resource allocation and alignment effects. *Journal of Management Information Systems* 32, 2 (2015), 8–39.

[25] Amy C Edmondson and Ingrid M Nembhard. 2009. Product development and learning in project teams: The challenges are the benefits. *Journal of product innovation management* 26, 2 (2009), 123–138.

[26] Massimo Egidi and Alessandro Narduzzo. 1997. The emergence of path-dependent behaviors in cooperative contexts. *International Journal of Industrial Organization* 15, 6 (1997), 677–709.

[27] Amany Elbanna and Ayomikun Idowu. 2021. Crowdwork, digital liminality and the enactment of culturally recognised alternatives to Western precarity: beyond epistemological terra nullius. *European Journal of Information Systems* 00, 00 (2021), 1–17. https://doi.org/10.1080/0960085X.2021.1981779

[28] Enrique Estellés and Fernando González. 2012. Towards an integrated crowdsourcing definition. *Journal of Information Science* X (2012), 1–22.

[29] Yulin Fang and Derrick Neufeld. 2008. Understanding sustained participation in open source software projects. *Journal of Management Information Systems* 25, 4 (2008), 9–50. https://doi.org/10.2753/MIS0742-1222250401

[30] Molly Q. Feldman and Brian James McInnis. 2021. How We Write with Crowds. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW3 (2021), 1–31. https://doi.org/10.1145/3432928

[31] Eureka Foong, Nicholas Vincent, Brent Hecht, and Elizabeth M. Gerber. 2018. Women (still) ask for less: Gender differences in hourly rate in an online labor marketplace. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018). https://doi.org/10.1145/3274322

[32] Jacob G. Foster, Andrey Rzhetsky, and James A. Evans. 2015. Tradition and Innovation in Scientists' Research Strategies. *American Sociological Review* 80, 5 (2015), 875–908. https://doi.org/10.1177/0003122415601618 arXiv:1302.6906

[33] Nikolaus Franke and Sonali Shah. 2003. How communities support innovative activities: An exploration of assistance and sharing among end-users. *Research Policy* 32, 1 (2003), 157–178. https://doi.org/10.1016/S0048-7333(02)00006-9

[34] Frédéric Fréry, Xavier Lecocq, and Vanessa Warnier. 2015. Competing with ordinary resources. *MIT Sloan Management Review* 56, 3 (2015), 69–77.

[35] Johann Füller, Katja Hutter, Julia Hautz, and Kurt Matzler. 2014. User roles and contributions in innovation-contest communities. *Journal of Management Information Systems* 31, 1 (2014), 273–308. https://doi.org/10.2753/MIS0742-1222310111

[36] Marian Garcia Martinez. 2017. Inspiring crowdsourcing communities to create novel solutions: Competition design and the mediating role of trust. *Technological Forecasting and Social Change* 117 (2017), 296–304. https://doi.org/10.1016/j.techfore.2016.11.015

[37] Diego Gómez-Zará, Leslie A. DeChurch, and Noshir S. Contractor. 2020. A Taxonomy of Team-Assembly Systems: Understanding How People Use Technologies to Form Teams. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2 (2020), 181:1–36. https://doi.org/10.1145/3415252

[38] Mary L. Gray, Syed Shoaib Ali, Siddharth Suri, and Deepti Kulkarni. 2016. The crowd is a collaborative network. *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW* 27 (2016), 134–147. https://doi.org/10.1145/2818048.2819942

[39] Jungpil Hahn, Jae Yun Moon, and Chen Zhang. 2008. Emergence of new project teams from open source software developer networks: Impact of prior collaboration ties. *Information Systems Research* 19, 3 (2008), 369–391.

[40] Aniko Hannak, Alan Mislove, Claudia Wagner, Markus Strohmaier, David Garcia, and Christo Wilson. 2017. Bias in Online freelance marketplaces: Evidence from TaskRabbit and Fiverr. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW*. 1914–1933. https://doi.org/10.1145/2998181.2998327

[41] Alexa M. Harris, Diego Gómez-Zará, Leslie A. DeChurch, and Noshir S. Contractor. 2019. Joining Together Online:The Trajectory of CSCW Scholarship on Group Formation. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–27. https://doi.org/10.1145/3359250

[42] Emily M. Hastings, Farnaz Jahanbakhsh, Karrie Karahalios, Darko Marinov, and Brian P. Bailey. 2018. Structure or nurture? The effects of team-building activities and team composition on team outcomes. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018). https://doi.org/10.1145/3274337

[43] Hideaki Hata, Mingyu Guo, and M. Ali Babar. 2017. Understanding the Heterogeneity of Contributors in Bug Bounty Programs. In *2017 ACM/IEEE International Symposium on Empirical Software Engineering and Measurement (ESEM)*. 223–228. https://doi.org/10.1109/ESEM.2017.34 arXiv:1709.06224

[44] Reto Hofstetter, Suleiman Aryobsei, and Andreas Herrmann. 2018. Should You Really Produce What Consumers Like Online? Empirical Evidence for Reciprocal Voting in Open Innovation Contests. *Journal of Product Innovation Management* 35, 2 (2018), 209–229. https://doi.org/10.1111/jpim.12382

[45] Bas Hofstra, Vivek V. Kulkarni, Sebastian Munoz Najar Galvez, Bryan He, Dan Jurafsky, and Daniel A. McFarland. 2020. The diversity–innovation paradox in science. *Proceedings of the National Academy of Sciences of the United States of America* 117, 17 (2020), 9284–9291. https://doi.org/10.1073/pnas.1915378117

[46] Keman Huang, Jinhui Yao, and Ming Yin. 2019. Understanding the skill provision in gig economy from a network perspective: A case study of fiverr. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 132:1–23. https://doi.org/10.1145/3359234

[47] Keman Huang, Jinhui Yao, Jia Zhang, and Zhiyong Feng. 2019. When Human Service Meets Crowdsourcing: Emerging in Human Service Collaboration. *IEEE Transactions on Services Computing* 12, 3 (2019), 460–473. https://doi.org/10.1109/TSC.2018.2810067

[48] Yun Huang, Yifeng Huang, Na Xue, and Jeffrey P Bigham. 2017. Leveraging complementary contributions of different workers for efficient crowdsourcing of video captions. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. 4617–4626.

[49] Katja Hutter, Julia Hautz, Julia Mueller, Johann Füller, and Kurt Matzler. 2010. Communitition: The tension between competition and collaboration in community based design contests. In *International Product Development Management Conference*. 1–33.

[50] Lilly C. Irani and M. Six Silberman. 2013. Turkopticon: Interrupting worker invisibility in Amazon Mechanical Turk. *Conference on Human Factors in Computing Systems - Proceedings* (2013), 611–620. https://doi.org/10.1145/2470654.2470742

[51] Nura Jabagi, Anne Marie Croteau, Luc K. Audebrand, and Josianne Marsan. 2019. Gig-workers' motivation: thinking beyond carrots and sticks. *Journal of Managerial Psychology* 34, 4 (2019), 192–213. https://doi.org/10.1108/JMP-06-2018-0255

[52] Mohammad Hossein Jarrahi, Will Sutherland, Sarah Beth Nelson, and Steve Sawyer. 2020. Platformic Management, Boundary Resources for Gig Work, and Worker Autonomy. *Computer Supported Cooperative Work: CSCW: An International Journal* 29, 1-2 (2020), 153–189. https://doi.org/10.1007/s10606-019-09368-7

[53] Hanieh Javadi Khasraghi and Rudy Hirschheim. 2021. Collaboration in crowdsourcing contests: how different levels of collaboration affect team performance. *Behaviour and Information Technology* 0, 0 (2021), 1–17. https://doi.org/10.1080/0144929X.2021.1887354

[54] Bertrand Jayles, Hye rin Kim, Ramón Escobedo, Stéphane Cezera, Adrien Blanchet, Tatsuya Kameda, Clément Sire, and Guy Theraulaz. 2017. How social information can improve estimation accuracy in human groups. *Proceedings of the National Academy of Sciences of the United States of America* 114, 47 (2017), 12620–12625. https://doi.org/10.1073/pnas.1703695114

[55] Julie Jiang, Danaja Maldeniya, Kristina Lerman, and Emilio Ferrara. 2021. The Wide, the Deep, and the Maverick. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–26. https://doi.org/10.1145/3449290

[56] Zhou Jiang and Xiaowen Hu. 2016. Knowledge Sharing and Life Satisfaction: The Roles of Colleague Relationships and Gender. *Social Indicators Research* 126, 1 (2016), 379–394. https://doi.org/10.1007/s11205-015-0886-9

[57] Gerald C Kane and Stephen P Borgatti. 2011. Centrality-IS proficiency alignment and workgroup performance. *MIS quarterly* (2011), 1063–1078.

[58] Otto Kässi and Vili Lehdonvirta. 2018. Online labour index: Measuring the online gig economy for policy and research. *Technological Forecasting and Social Change* 137, July (2018), 241–248. https://doi.org/10.1016/j.techfore.2018.07.056

[59] By Lawrence F Katz and Alan B Krueger. 2017. The role of unmeployment in the rise in alternative work arrangements. *American Economic Reviews* 107, 5 (2017), 388–392.

[60] Charles Kiene, Aaron Shaw, and Benjamin Mako Hill. 2018. Managing organizational culture in online group mergers. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018). https://doi.org/10.1145/3274358

[61] Young Ji Kim, David Engel, Anita Williams Woolley, Jeffrey Yu Ting Lin, Naomi McArthur, and Thomas W. Malone. 2017. What makes a strong team? Using collective intelligence to predict team performance in League of Legends. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW*. 2316–2329. https://doi.org/10.1145/2998181.2998185

[62] Aniket Kittur, Jeffrey V. Nickerson, Michael S. Bernstein, Elizabeth M. Gerber, Aaron Shaw, John Zimmerman, Matthew Lease, and John J. Horton. 2013. The Future of Crowd Work. In *CSCW'13*. 1301–1317. https://doi.org/10.1145/2441776.2441923

[63] Yasemin Y Kor and Chamu Sundaramurthy. 2009. Experience-based human capital and social capital of outside directors. *Journal of management* 35, 4 (2009), 981–1006.

[64] Asher Koriat. 2012. When are two heads better than one and why. *Science* 336, April (2012), 20–22.

[65] Airi Lampinen and Barry Brown. 2017. Market design for HCI: Successes and failures of peer-to-peer exchange platforms. *Conference on Human Factors in Computing Systems - Proceedings* 2017-May (2017), 4331–4343. https://doi.org/10.1145/3025453.3025515

[66] Alex Leavitt, Brian C Keegan, and Joshua Clark. 2016. Ping to win? Non-verbal communication and team performance in competitive online multiplayer games. In *Conference on Human Factors in Computing Systems - Proceedings*. 4337–4350. https://doi.org/10.1145/2858036.2858132

[67] Ho Cheung Brian Lee, Sulin Ba, Xinxin Li, and Jan Stallaert. 2018. Salience bias in crowdsourcing contests. *Information Systems Research* 29, 2 (2018), 401–418. https://doi.org/10.1287/isre.2018.0775

[68] Vili Lehdonvirta. 2016. Space, Place and Global Digital Work. *Space, Place and Global Digital Work* (2016). https://doi.org/10.1057/978-1-137-48087-3

[69] Jurgen Lerner and Alessandro Lomi. 2018. Diverse teams tend to do good work in wikipedia (but jacks of all trades don't). In *Proceedings of the 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM 2018*. 214–221. https://doi.org/10.1109/ASONAM.2018.8508597

[70] Guo Li, Haiyi Zhu, Tun Lu, Xianghua Ding, and Ning Gu. 2015. Is It good to be like wikipedia?: Exploring the trade-offs of introducing collaborative editing model to QandA Sites. *CSCW 2015 - Proceedings of the 2015 ACM International Conference on Computer-Supported Cooperative Work and Social Computing* (2015), 1080–1091. https://doi.org/10.1145/2675133.2675155

[71] Jan Lorenz, Heiko Rauhut, Frank Schweitzer, and Dirk Helbing. 2011. How social influence can undermine the wisdom of crowd effect. *Proceedings of the National Academy of Sciences of the United States of America* 108, 22 (2011), 9020–9025. https://doi.org/10.1073/pnas.1008636108

[72] Ioanna Lykourentzou, Robert E Kraut, and Steven P Dow. 2017. Team dating leads to better online ad hoc collaborations. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW*. 2330–2343. https://doi.org/10.1145/2998181.2998322

[73] Anoush Margaryan. 2019. Comparing crowdworkers' and conventional knowledge workers' self-regulated learning strategies in the workplace. *Human Computation* 6 (2019), 83–97. https://doi.org/10.15346/hc.v6i1.5

[74] Anoush Margaryan. 2019. Workplace learning in crowdwork: Comparing microworkers' and online freelancers' practices. *Journal of Workplace Learning* 31, 4 (2019), 250–273. https://doi.org/10.1108/JWL-10-2018-0126

[75] Luis L Martins, Lucy L Gilson, and M Travis Maynard. 2004. Virtual teams: What do we know and where do we go from here? *Journal of management* 30, 6 (2004), 805–835.

[76] Benjamí Martorell, Lidunka Vočădlo, John Brodholt, and Ian G. Wood. 2013. Atypical Combinations and Scientific Impact. *Science* 342, 6157 (2013), 466–468.

[77] Winter Mason and Duncan J. Watts. 2012. Collaborative learning in networks. *Proceedings of the National Academy of Sciences of the United States of America* 109, 3 (2012), 764–769. https://doi.org/10.1073/pnas.1110069108

[78] Brian McInnis, Dan Cosley, Chaebong Nam, and Gilly Leshed. 2016. Taking a hit: Designing around rejection, mistrust, risk, and workers' experiences in Amazon Mechanical Turk. In *Conference on Human Factors in Computing Systems - Proceedings*. 2271–2282. https://doi.org/10.1145/2858036.2858539

[79] Joseph S McIntyre. 2011. Effectiveness of three case studies and associated teamwork in stimulating freshman interest in an introduction to engineering course. *Journal of STEM Education: Innovations and Research* 12, 7 (2011).

[80] Lev Muchnik, Sinan Aral, and Sean J. Taylor. 2013. Social influence bias: A randomized experiment. *Science* 341, 6146 (2013), 647–651. https://doi.org/10.1126/science.1240466

[81] Joaquin Navajas, Tamara Niella, Gerry Garbulsky, Bahador Bahrami, and Mariano Sigman. 2018. Aggregated knowledge from a small number of debates outperforms the wisdom of large crowds. *Nature Human Behaviour* 2, 2 (2018), 126–132. https://doi.org/10.1038/s41562-017-0273-4 arXiv:1703.00045

[82] Frank M.H. Neffke. 2019. The value of complementary co-workers. *Science Advances* 5, 12 (2019). https://doi.org/10.1126/sciadv.aax3370

[83] Laurie Miller Nelson. 2013. Collaborative problem solving. *Instructional-Design Theories and Models: A New Paradigm of Instructional Theory* 2 (2013), 241–267. https://doi.org/10.4324/9781410603784-17

[84] Ekaterina Nemkova, Pelin Demirel, and Linda Baines. 2019. In search of meaningful work on digital freelancing platforms: the case of design professionals. *New Technology, Work and Employment* 34, 3 (2019), 226–243. https://doi.org/10.1111/ntwe.12148

[85] Dorit Nevo and Julia Kotlarsky. 2020. Crowdsourcing as a strategic IS sourcing phenomenon: Critical review and insights for future research. *Journal of Strategic Information Systems* 29, 4 (2020), 101593. https://doi.org/10.1016/j.jsis.2020.101593

[86] Oded Nov, Mor Naaman, and Chen Ye. 2009. Motivational, Structural and Tenure Factors that Impact Online Community Photo Sharing. In *The 3rd International Conference on Weblogs and Social Media (ICWSM 2009)*. 138–145.

[87] Lora Oehlberg, Jasmine Jones, Alice Agogino, and Björn Hartmann. 2012. Dazzle: Supporting framing in co-located design teams through remote collaboration tool. *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW* (2012), 183–186. https://doi.org/10.1145/2141512.2141573

[88] Edward L. Platt and Daniel M. Romero. 2018. Network structure, efficiency, and performance in wikiprojects. In *12th International AAAI Conference on Web and Social Media, ICWSM 2018*, Vol. 13. 251–260. https://doi.org/10.1177/

1745691617697078 arXiv:1804.03763

[89] Huilian Sophie Qiu, Alexander Nolte, Anita Brown, Alexander Serebrenik, and Bogdan Vasilescu. 2019. Going Farther Together: The Impact of Social Capital on Sustained Participation in Open Source. *Proceedings - International Conference on Software Engineering* 2019-May (2019), 688–699. https://doi.org/10.1109/ICSE.2019.00078

[90] Ray Reagans, Linda Argote, and Daria Brooks. 2005. Individual experience and experience working together: Predicting learning rates from knowing who knows what and knowing how to work together. *Management science* 51, 6 (2005), 869–881.

[91] Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence embeddings using siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. 3982–3992. https://doi.org/10.18653/v1/d19-1410 arXiv:1908.10084

[92] Daniel M. Romero, Dan Huttenlocher, and Jon Kleinberg. 2015. Coordination and efficiency in decentralized collaboration. In *Proceedings of the 9th International Conference on Web and Social Media, ICWSM 2015*. 367–376. arXiv:1503.07431

[93] Niloufar Salehi and Michael S. Bernstein. 2018. HIVe: Collective design through network rotation. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018). https://doi.org/10.1145/3274420

[94] Niloufar Salehi, Andrew McCabe, Melissa Valentine, and Michael S Bernstein. 2017. Huddler: Convening stable and familiar crowd teams despite unpredictable availability. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW*. 1700–1713. https://doi.org/10.1145/2998181.2998300

[95] Niloufar Salehi, Jaime Teevan, Shamsi Iqbal, and Ece Kamar. 2017. Communicating context to the Crowd for complex writing tasks. *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW* (2017), 1890–1901. https://doi.org/10.1145/2998181.2998332

[96] Mareike Seifried, Roman Jurowetzki, and Tobias Kretschmer. 2021. Career Paths in Online Labor Markets: Same, Same but Different? *SSRN Electronic Journal* (2021). https://doi.org/10.2139/ssrn.3774773

[97] Andreas Seufert, Georg Von Krogh, and Andrea Bach. 1999. Towards knowledge networking. *Journal of Knowledge Management* 3, 3 (1999), 180–190. https://doi.org/10.1108/13673279910288608

[98] Elham Shafiei Gol, Mari Klara Stein, and Michel Avital. 2019. Crowdwork platform governance toward organizational value creation. *Journal of Strategic Information Systems* 28, 2 (2019), 175–195. https://doi.org/10.1016/j.jsis.2019.01.001

[99] Richard M. Smedley and Neil S. Coulson. 2021. A practical guide to analysing online support forums. *Qualitative Research in Psychology* 18, 1 (2021), 76–103. https://doi.org/10.1080/14780887.2018.1475532

[100] Fabian Stephany. 2020. When Does it Pay Off to Learn a New Skill? Revealing the Complementary Benefit of Cross-Skilling. (2020), 1–25. arXiv:2010.11841 http://arxiv.org/abs/2010.11841

[101] James Surowiecki. 2005. *The wisdom of crowds*. 336 pages. https://doi.org/10.1016/S0140-6736(16)31130-8

[102] Yla Tausczik and Ping Wang. 2017. To share, or not to share? Community-level collaboration in open innovation contests. *Proceedings of the ACM on Human-Computer Interaction* 1, CSCW (2017). https://doi.org/10.1145/3134735

[103] Yla Tausczik and Ping Wang. 2017. To Share, or Not to Share? Community-Level Collaboration in Open Innovation Contests. *Proc. ACM Hum.-Comput. Interact.* 1, CSCW, Article 100 (dec 2017), 23 pages. https://doi.org/10.1145/3134735

[104] Christian Terwiesch and Yi Xu. 2008. Innovation contests, open innovation, and multiagent problem solving. *Management science* 54, 9 (2008), 1529–1543.

[105] Chien Wen Tina Yuan, Hao Chuan Wang, Yu Hsuan Liu, and Yuan Chi Tseng. 2019. Gender effects on collaborative online brainstorming teamwork. In *Conference on Human Factors in Computing Systems - Proceedings*. 1–6. https://doi.org/10.1145/3290607.3312989

[106] Gustavo Umbelino, Matin Yarmand, Samuel Blake, Vivian Ta, Amy Luo, and Steven P Dow. 2021. ProtoTeams: Supporting Team Dating in Co-Located Settings. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW3 (2021). https://doi.org/10.1145/3434182

[107] Maya Usher and Miri Barak. 2020. Team diversity as a predictor of innovation in team projects of face-to-face and online learners. *Computers and Education* 144, March 2019 (2020), 103702. https://doi.org/10.1016/j.compedu.2019.103702

[108] Vili Lehdonvirta, Anoush Margaryan, and Huw Davies. 2018. *Literature Review: Skills Formation and Skills Matching in Online Platform Work: Policies and Practices for Promoting Crowdworkers' Continuous Learning (CrowdLearn)*. Technical Report. European Center for the Development of Vocational Training (CEDEFOP). 1–27 pages. https://www.cedefop.europa.eu/files/crowdlearn_literature_review.pdf

[109] Gerit Wagner, Julian Prester, and Guy Paré. 2021. Exploring the boundaries and processes of digital platforms for knowledge work: A review of information systems research. *Journal of Strategic Information Systems* 30, 4 (2021), 1–26. https://doi.org/10.1016/j.jsis.2021.101694

[110] Juliet Webster. 2016. Microworkers of the Gig Economy: Separate and Precarious. *New Labor Forum* 25, 3 (2016), 56–64. https://doi.org/10.1177/1095796016661511

[111] Miaomiao Wen, Keith Maki, Steven P. Dow, James Herbsleb, and Carolyn Rose. 2017. Supporting virtual team formation through community-wide deliberation. *Proceedings of the ACM on Human-Computer Interaction* 1, CSCW

(2017). https://doi.org/10.1145/3134744

[112] Mark E. Whiting, Dilrukshi Gamage, Snehalkumar S. Gaikwad, Aaron Gilbee, Shirish Goyal, Alipta Ballav, Dinesh Majeti, Nalin Chhibber, Angela Richmond-Fuller, Freddie Vargus, Tejas Seshadri Sarma, Varshine Chandrakanthan, Teogenes Moura, Mohamed Hashim Salih, Gabriel Bayomi Tinoco Kalejaiye, Adam Ginzberg, Catherine A. Mullings, Yoni Dayan, Kristy Milland, Henrique Orefice, Jeff Regino, Sayna Parsi, Kunz Mainali, Vibhor Sehgal, Sekandar Matin, Akshansh Sinha, Rajan Vaish, and Michael S. Bernstein. 2017. Crowd guilds: Worker-led reputation and feedback on crowdsourcing platforms. *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW* (2017), 1902–1913. https://doi.org/10.1145/2998181.2998234 arXiv:1611.01572

[113] Alex J. Wood, Mark Graham, Vili Lehdonvirta, and Isis Hjorth. 2019. Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy. *Work, Employment and Society* 33, 1 (2019), 56–75. https://doi.org/10.1177/0950017018785616

[114] Robert E Wood. 1986. Task complexity: Definition of the construct. *Organizational behavior and human decision processes* 37, 1 (1986), 60–82.

[115] Lingfei Wu, Dashun Wang, and James A. Evans. 2019. Large teams develop and small teams disrupt science and technology. *Nature* 566, 7744 (2019), 378–382. https://doi.org/10.1038/s41586-019-0941-9

[116] Wenjun Wu, Wei Tek Tsai, and Wei Li. 2013. An evaluation framework for software crowdsourcing. *Frontiers of Computer Science* 7, 5 (2013), 694–709. https://doi.org/10.1007/s11704-013-2320-2

[117] Stefan Wuchty, Benjamin F. Jones, and Brian Uzzi. 2007. The increasing dominance of teams in production of knowledge. *Science* 316, 5827 (2007), 1036–1039. https://doi.org/10.1126/science.1136099

[118] Chun Lei Yang, Mao Long Xu, Juanjuan Meng, and Fang Fang Tang. 2017. Efficient Large-Size Coordination Via Voluntary Group Formation: an Experiment. *International Economic Review* 58, 2 (2017), 651–668. https://doi.org/10.1111/iere.12230

[119] Yang Yang, PY Chen, and Rajiv Banker. 2010. Impact of past performance and strategic bidding on winner determination of open innovation contest. In *Workshop on Information Systems and Economics (WISE 2010)*, Vol. 2010. 11–2.

[120] Yang Yang, Pei-yu Chen, and Paul A Pavlou. 2009. Open Innovation: Strategic Design of Online Contests. In *International Conference on Information Systems*. 1–16.

[121] Zheng Yao, Silas Weden, Lea Emerlyn, Haiyi Zhu, and Robert E. Kraut. 2021. Together but Alone: Atomization and Peer Support among Gig Workers. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021). https://doi.org/10.1145/3479535

[122] Hua (Jonathan) Ye and Atreyi Kankanhalli. 2017. Solvers' participation in crowdsourcing platforms: Examining the impacts of trust, and benefit and cost factors. *Journal of Strategic Information Systems* 26, 2 (2017), 101–117. https://doi.org/10.1016/j.jsis.2017.02.001

[123] Kimberly Michelle Ying, Fernando J. Rodriguez, Alexandra Lauren Dibble, and Kristy Elizabeth Boyer. 2021. Understanding Women's Remote Collaborative Programming Experiences. In *Proceedings of the ACM on Human-Computer Interaction*, Vol. 4. 1–29. https://doi.org/10.1145/3432952

[124] Alexey Zagalsky, Daniel M. German, Margaret Anne Storey, Carlos Gómez Teshima, and Germán Poo-Caamaño. 2018. How the R community creates and curates knowledge: an extended study of stack overflow and mailing lists. *Empirical Software Engineering* 23, 2 (2018), 953–986. https://doi.org/10.1007/s10664-017-9536-y

[125] Mingyi Zhao, Jens Grossklags, and Peng Liu. 2015. An empirical study of web vulnerability discovery ecosystems. In *Proceedings of the ACM Conference on Computer and Communications Security*, Vol. 2015-Octob. 1105–1117. https://doi.org/10.1145/2810103.2813704

[126] Haichao Zheng, Dahui Li, and Wenhua Hou. 2011. Task design, motivation, and participation in crowdsourcing contests. *International Journal of Electronic Commerce* 15, 4 (2011), 57–88.

[127] Minghui Zhou and Audris Mockus. 2012. What make long term contributors: Willingness and opportunity in OSS community. In *Proceedings - International Conference on Software Engineering*. 518–528. https://doi.org/10.1109/ICSE.2012.6227164

[128] Sharon Zhou, Melissa Valentine, and Michael S. Bernstein. 2018. In search of the Dream Team: Temporally constrained multi-armed bandits for identifying effective team structures. *Conference on Human Factors in Computing Systems - Proceedings* 2018-April (2018). https://doi.org/10.1145/3173574.3173682

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