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Submitting tentative solutions for platform feedback in crowdsourcing contests: breaking network closure with boundary spanning for team performance

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Submitting Tentative Solutions for Platform Feedback in Crowdsourcing Contests: Breaking Network Closure with Boundary Spanning for Team Performance

Abstract

Purpose – To obtain optimal deliverables, more and more crowdsourcing platforms allow contest teams to submit tentative solutions and update scores/rankings on public leaderboards. Such feedback-seeking behavior for progress benchmarking pertains to the team representation activity of boundary spanning. The literature on virtual team performance primarily focuses on team characteristics, among which network closure is generally considered a positive factor. This study further examines how boundary spanning helps mitigate the negative impact of network closure.

Design/methodology/approach – This sudy collected data of 9,793 teams in 246 contests from Kaggle.com. Negative binomial regression modeling and linear regression modeling are employed to investigate the relationships among network closure, boundary spanning, and team performance in crowdsourcing contests.

Findings – Whereas network closure turns out to be a negative asset for virtual teams to seek platform feedback, boundary spanning mitigates its impact on team performance. On top of such a partial mediation, boundary spanning experience and previous contest performance serve as potential moderators.

Practical implications –The findings offer helpful implications for researchers and practitioners on how to break network closure and encourage boundary spanning with the establishment of facilitating structures in crowdsourcing contests.

Originality/value – The study advances the understanding of theoretical relationships among network closure, boundary spanning, and team performance in crowdsourcing contests.

Keywords Crowdsourcing Contests, Network Closure, Boundary Spanning, Team Performance

Paper type Research

1. Introduction

The advances in Internet-based platforms give rise to new organizational sourcing models. Increasingly used worldwide, crowdsourcing allows organizations to recruit external experts to perform creative tasks via online platforms (Redi et al. 2013; Hsiang and Rayz 2020; Shi, Pan, and Shan 2021). In this way, organizations may acquire expertise from uniquely skilled workforce beyond their boundaries to solve technical and operational problems (Chiu, Liang, and Turban 2014; Nevo and Kotlarsky 2020; Lissillour and Sahut 2021). Thus, crowdsourcing is a strategic move leading to organizational innovation, competitive advantage, and HR cost reduction (Gol, Stein, and Avital 2019; Jespersen 2018).

There are two types of crowdsourcing platforms: company-hosted and intermediary-based. As for the former, an enterprise creates its own platform (e. g., Dells' IdeaStorm, Threadless' Design Challenges, LEGO Ideas, Nokia's IdeasProject) and interacts directly with the crowd for an ongoing supply of quality ideas (Bakici 2020; Bayus 2013; Blohm et al. 2018). As for the latter, companies use various third-party crowdsourcing platforms (e.g., Innocentive for research and development, Kaggle for predictive modeling projects, TopCoder for software development projects, Ninesigma for open innovation, 99designs for graphic design, Atizo for idea innovation, and CrowdSpring for industrial design and copywriting) to interact with free-lancer workers (Bakici 2020; Blohm et al. 2018; Jin et al. 2021). The management of the whole process by the intermediaries obviates the risks and overhead associated with company-hosted crowdsourcing. Therefore, most small and medium enterprises source problem solutions through third-party providers to address human resource shortage (Marjanovic, Fry, and Chataway 2012; Zhao and Zhu 2014).

Crowdsourcing contests emerge as the primary means to solicit high-quality ideas and solutions from the crowd (Di Gangi and Wasko 2009). For such contests, crowdsourcing platforms let individual users team up and offer monetary reward to the winning groups that provide the best solutions (Archak 2010; DiPalantino and Vojnovic 2009; Liu et al. 2014; Pee, Koh, and Goh 2018). Compared with distributed project teamwork within traditional corporate boundaries, virtual teamwork in an ad hoc manner is more challenging, as it involves fluid social capital and intellectual capital when crowd members corporate and compete with each other at the same time

(Dissanayake, Zhang, and Gu 2015). Thus the understanding of such group dynamics is essential to the enhancement of team performance in crowdsourcing settings.

To elicit quality solutions, in particular, more and more crowdsourcing platforms like TopCoder, Kaggle, and TaskCn allow contest teams to submit tentative solution before final deadlines and provide feedback in form of scores and rankings on public leaderboard. Little is known about the role that such a boundary spanning activity plays in determining crowdsourcing contest outcome, as the extant research on virtual team performance primarily focuses on team characteristics. In addition, what is proven for distributed project teamwork may not work as well for crowdsourcing contests. Capturing a virtual team's social capital in terms of how members are closely knitted in their social ties with each other, network closure is believed conducive to team performance (Wu et al. 2020). In crowdsourcing contests, however, it is not necessarily a positive asset. The high-level network closure of an ad hoc team may boost members' sense of self-sufficiency and limit their boundary spanning effort to reach out for external resources.

For crowdsourcing platform design and contest team building, it is essential to address the following question: how network closure and boundary spanning activities affects team performance in crowdsourcing contests? However, the current literature provides little hint about virtual team dynamics involving network closure and boundary spanning behavior. As such, the objective of this study is to attain an evidence-based understanding of the relationships among network closure, boundary spanning and team performance considering past crowdsourcing contest experiences. Empirical findings will help fill in the literature gap and enhance crowdsourcing outcome. To promote crowdsourcing effectiveness, contest organizers may consider participants' prior ties, behavior trajectory and past performance. Proper platform facilitation is conducive to team building and performance by establishing appropriate structures for network closure and boundary spanning.

The remainder of this article is organized as follows. First, it reviews the literature concerning the phenomenon and identifies relevant research variables. Then, it hypothesizes the relationships among the variables in form of a research model. Empirical observations collected from a crowdsourcing platform are used to evaluate the model. Statistical results are discussed, followed by the conclusion and implications.

2. Research Background

To facilitate continuous improvement of solutions, more and more crowdsourcing platforms allow teams to make tentative submissions for feedback. For instance, Kaggle evaluates analytic solutions with the test dataset provided by each contest host: a random 30% of data is used for generating preliminary scores of tentative solutions on the leaderboard, whereas the rest 70% is used to determine the final rankings. The use of partial test data for the evaluation of tentative solutions is to avoid adaptive overfitting that leads to overly optimistic estimates of model performance from repetitive model evaluation with full data (Dwork et al. 2015).

To each contest team, the feedback that it acquires from the platform with tentative submissions is helpful for continuous improvement. Such an outreach activity constitutes boundary spanning, defined as "the team's or group's effort to establish and manage interactions with parties in the external environment that enhance the team and others linked to the team in meeting performance goals" (Van Osch and Steinfield 2018, P. 651). The concept originates in the literature on corporapte projects (e.g., new product development) to explain the positive relationship between team performance and external interaction (Ancona and Caldwell 1992). Over the years, researchers identify three types of boundary spanning activities: team representation (e.g., seeking feedback on team progress), task coordination (e.g., communicating plans with other teams), and information search (e.g., consulting helpdesks) (Bigliardi, Ivo Dormio, and Galati 2012; Marrone 2010; Van Osch and Steinfield 2018). Boundary spanning is found essential to team functionalities that rely on external resources, especially shared learning and knowledge transfer (Van Osch and Steinfield 2018).

In crowdsourcing contests, teams must effectively coordinate cross-boundary efforts and manage external relationships to handle task complexity, competitive pressure, and time constraint (Füller et al. 2014; Hutter et al. 2011). Extant studies primarily investigate how virtual teams share external knowledge through means like forum discussions to enhances individual and team performances (Bullinger et al. 2010; Hutter et al. 2011; Javadi Khasraghi and Hirschheim 2021). However, such subjective comments are unreliable in comparison to the quantitative evalution of provided by crowdsourcing platforms. If teams receive feedback on their proposed solutions from a platform, they can identify problems and make improvement (Boons, Stam, and Barkema 2015).

Furthermore, such an experience helps team members enhance their skills for future contests (Leimeister et al. 2009; Nov, Naaman, and Ye 2010).

Researchers recognize the importance of boundary spanning in different contexts from global organizations to open innovation communities (Ancona and Caldwell 1992; Fleming and Waguespack 2007; Schotter et al. 2017). Yet few have addressed the team boundary spanning phenomenon on crowdsourcing contest platforms. On other types of online platforms, various boundary spanning activities are identified, such as asking for help from other community members, consulting with experts, and sharing work with others to get feedback (Füller et al. 2014; Hutter et al. 2011). For crowdsourcing contests, one type of boundary spanning activities is of particular interest: seeking platform feedback on tentative solutions. This study attempts to examine the role that such a behavior plays in affecting team performance.

Indicating the extent to which meaningful relationships exist in a social network, network closure is often used as a team characteristic to predict collaborative effectiveness in various contexts such as face-to-face teams (Balkundi and Harrison 2006), mutual monitoring contracts (Towry 2003), startup bootcamps (Hasan and Koning 2019), and entrepreneurial innovations (Ruef 2002). Nevertheless, the effects of network closure are mixed: some studies confirm its positive relationship with team performance (Nahapiet and Ghoshal 1998; Wu et al. 2020), but others suggest that network closure leads to information exchange redundancy that constrains knowledge building (Burt and others 2005; Oh, Chung, and Labianca 2004).

In a group, members develop communicative norms and collaborative routines over time (De Jong, De Ruyter, and Wetzels 2005). Once teammates get familiar with each other's workstyle, they tend to establish certain job procedures for all to follow (Ku, Wei, and Akarasriworn 2013). For a crowdsourcing contest, therefore, members who have teamed up previously are quicker to build up group rapport and agree upon implicit rules.

Prior studies focus on network closure in non-competitive settings (e.g. startup bootcamps and entrepreneurial teams), in which each team's performance is evaluated independently (Hasan and Koning 2019; Ruef 2002). In competitive settings, however, teams are ranked agaist each other based on certain criteria regarding their deliverables (Blohm et al. 2018). Such social comparison may cause a team of high network closure to reduce boundary spanning activities (Bartel 2001).

As the role that network closure plays in team functioning is context-dependent, it demands an in-depth investigation with regards to crowdsourcing contests.

Researchers have examined the influencing factors of boundary spanning in regard to individuals (e.g., role responsibility and confidence), teams (e.g., team composition and leadership), and the environment (e.g., resources and training) (Ancona and Caldwell 2009; Edmondson 1999; Marrone, Tesluk, and Carson 2007). However, little is known about the boundary spanning behavior in crowdsourcing contests, though more and more platforms allow teams to submit tentative solutions for feedback in form of scores and ranks. Such feedback-seeking behavior constitutes team representation (Van Osch and Steinfield 2018), one major type of boundary spanning that this study focuses on in the examination of its relationships with network closure and team performance.

In crowdsourcing contests on analytics solutions, for instance, a platform like Kaggle provides teams the feedback on their intermediate submissions in form of performance scores from model evaluation with partial test datasets. Despite the accessibility of such an external resource, certain teams may still be hesitant about boundary spanning. In particular, a team with high network closure tends to rely more on its internal resources in terms of members' knowledge and experience due to mutual trust and support. Such a team is typically confident in its performance and does not want to give other teams hints about its progress. Table I compares the main research variables of this study including network closure, boundary spanning and team performance in the context of crowdsourcing contests with the same ones used in extant research on corporate projects.

Table I. Research Variables in Different Contexts

VARIABLE	CORPORATE PROJECT	CROWDSOURCING CONTEST
NETWORK CLOSURE	When project team members have high network closure, they work closely with each other in activities such as exploring external resources.	When ad hoc members of a virtual team have high network closure, they rely more on their collective experiences than seeking feedback from outside.
BOUNDARY SPANNING	There are three activities of boundary spanning: team representation, task coordination and information search.	Boundary spanning mainly takes the form of team representation in terms of seeking feedback on team progress.
TEAM PERFORMANCE	Team performance can be operationalized with different measures.	A crowdsourcing platform like Kaggle typically evaluates/ranks contest team performance with a uniform formula.

3. Research Model

This study develops a research model to investigate the relationships among network closure, boundary spanning, and team performance in crowdsourcing contests. The rationale is that network closure as a pre-existing condition affects boundary spanning behavior in the current contest, which makes a difference in team performance consequently. As summarized in Fig.1, boundary spanning partially mediates the influence of network closure on team performance. In addition, previous contest performance and boundary spanning experience serve as the moderators on the direct and indirect relationships.

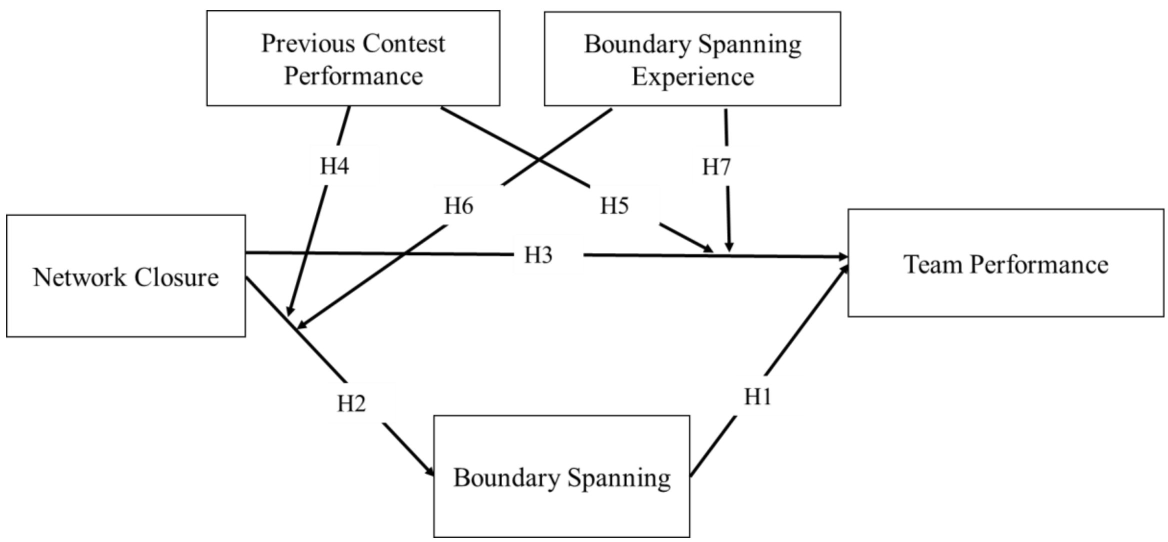

Fig.1. Research Model

The relationship between boundary spanning and team performance is quite well established in the literature. New-product development teams engaging in boundary spanning are likely successful and innovative as they effectively acquire external knowledge and expertise (Ancona and Caldwell, 1992). Consulting teams carrying out more boundary spanning activities have better understanding of client needs, leading to improved service quality (Ancona, 1990). In crowdsourcing contests, boundary spanning primarily takes the form of team representation when a team submits tentative solutions to the platform for feedback. After each submission, the team can see the evaluation as well as its standing against other teams in the contest. Based on such feedback as preliminary scores and rankings, the team can understand how well it is doing and improve the work accordingly. Previously, it was found that final scores helps team members understand their strengths and weaknesses for skill enhancement in future contests (Jiang, Huang, and Beil 2021). This study further posits that team outreach for platform feedback during a contest is conducive to eventual outcome.

Hypothesis 1: Boundary spanning positively affects team performance.

Most crowdsourcing contests demand collaborative effort for complex tasks, and the relationships among team members bear on their motivation for boundary spanning. Such relationships constitute social capital defined as "sum of the actual and potential resources embedded within, available through, and derived from ties within networks of social relationships" (Lee, Bachrach, and Lewis 2014). Social capital theory posits that the intangible resource residing with social ties is essential to collective endeavor (Nahapiet and Ghoshal 1998), as they indicate the likelihood that team members work well with one another (Dissanayake, Zhang, and Gu 2015). Stronger reciprocal ties enhance self-reliance among team members as they share knowledge and expertise with each other (Coleman 1990). Accordingly, network closure indicates the degree to which mutual identification among members promotes their social exchange (Reagans, Zuckerman, and McEvily 2004). In a crowdsourcing contest, therefore, team members of stronger network closure feel less need to reach beyond the team boundary for information but rely more on themselves. As a circumstantial evidence, organizations dependent on their embedded social ties tend to seal themselves off from external sources of new ideas (Uzzi 1996).

Hypothesis 2: Network closure negatively affects boundary spanning.

Although network closure is conducive to the creation of group norms, the establishment of mutual trust, and the exchange of member ideas, it has a detrimental effect on the quality of information acquired (Lee, Bachrach, and Lewis 2014). At the team, project, and organization levels, network closure is found a negative predictor of performance outcome due to exchange redundancy, as strong social ties hinder external information search (Burt 2009; Oh et al. 2004; Katz, 1982; Soda et al. 2004). In crowdsourcing contests, similarly, network closure is likely to compromise virtual team performance as a result of blocked information inflow. As the flip side of network closure in the social capital literature, structural holes help a team open up to knowledge and expertise beyond its own boundary (Reagans, Zuckerman, and McEvily 2004).

Hypothesis 3: Network closure negatively affects team performance.

It remains a question whether the “dark side” of network closure persists for teams with different prior experiences. A team’s previous exposure to similar challenges builds up its expertise and competence for later tasks (Guinan, Cooprider, and Faraj 1998). Meanwhile, a more experienced team is less motivated to learn from the outside, as members cultivate a higher level of self-efficacy (Haas and Hansen 2005). Such a positive “judgment of one’s ability to organize and execute given types of performances” (Bandura 1997) obviates the urgency for a crowdsourcing team to get external help in form of platform feedback. Thus, the relationship between network closure and boundary spanning is likely to be moderated by previous contest performance. Specially, the negative effect of network closure is expected to be stronger for teams with relatively high performance in the past.

Hypothesis 4: Previous contest performance moderates the relationship between network closure and boundary spanning.

In various settings such as virtual communities, academic projects, computer training, and IT usage, it is found that teammates’ prior performance shapes their self-efficacy that affect how they accomplish the current task (Easley, Devaraj, and Crant 2003; M. H. Hsu et al. 2007; Johnson and Marakas 2000; Sun, Fang, and Lim 2012). After each crowdsourcing contest, members of a team review its performance, which bears on their confidence for subsequent effort. A team comprising individuals who have been doing well on everage exhibits a relatively high level of collective self-efficacy that reinforces their best practices. Typically, successful teams are more open-minded as members believe in their capability to make things right with any resources available (Thoms, Moore , and Scott 1996). The relationship between self-efficacy for participating in self-managed work groups and the big five personality dimensions. Therefore, previous contest performance is likely to migitate the negative effect of network closure on team performance.

Hypothesis 5: Previous contest performance moderates the relationship between network closure and team performance.

Boundary spanning experience captures the extent to which each member’s last team improved its performance based on platform feedback on tentative solutions. To examine the relationships involving such a new experience, this study consults the literature on virtual community user behavior. Compared with experienced users, new comers have more difficulty in acquiring useful knowledge from a virtual community (W. Tsai and Ghoshal 1998). As virtual community members gain more experience, not only their platform- and task-related beliefs evolve (Karahanna, Straub, and Chervany 1999; Sun, Fang, and Lim 2012), but the antecedents to such beliefs become more or less influential as well (Chang et al. 2014). Users familiar with how things work in a virtual community are likely to seek information actively to meet task needs (Zha et al. 2015). In the crowdsourcing context, it is expected that a team with positive boundary spanning experience has a relatively firm belief in such a practice. Even if the team comprises the members who know each other well, it is still likely to seek external feedback by submitting tentative solutions to the platform. Therefore, it is hypothesized that the negative effect of network closure on boundary spanning to be smaller for teams positive boundary spanning experience.

Hypothesis 6: Boundary spanning experience moderates the relationship between network closure and boundary spanning.

People expand their knowledge through the accumulation of personal experiences (Bandura, 2009). Experienced members of an online community are found to make more quality contributions than novice members (H.-T. Tsai and Bagozzi 2014). In such a virtual enviornment, the acquirement of prior experience is regarded as one critical step of social learning process (Lampe and Johnston, 2007). In crowdsourcing contests, when a team finds that platform feedback on tentative solutions is helpful for the improvement of final submission, it will no longer be self-sufficing based on its own network closure. As positive boundary spanning experience encourages team members to seek external help, it weakens the negative impact of network closure on team performance. Thus, boundary spanning experience also moderates relationship between network closure and team performance.

Hypothesis 7: Boundary spanning experience moderates the relationship between network closure and team performance.

The widespread usage of crowdsourcing contests by organizations motivates a platform to enhance the design and facilitation of ideation processes. The hypothesized relationships, if verified, lead to a deeper understanding of behavioral patterns that are associated with positive crowdsourcing outcome. Keeping track of team performance and member participation, the fine-grained records captured by a crowdsourcing contest platform provide the opportunity for empirical investigation. The findings may help crowdsourcing sponsors improve contest configurations in form of feedback and rewarding mechanisms.

4. Research Design

To test the research model, this study collects data from a crowdsourcing platform that facilitates *ad hoc* teaming and boundary spanning for contest participants. Kaggle.com is an appropriate candidate as it lets users form teams for each contest and compete against each other. It also allows teams to submit tentative solutions before the contest deadline and provides feedback in form of score and ranking on the public leaderboard. Kaggle is the most popular crowdsourcing platform in the data science and machine learning area. Having over 5 million registered users from 194 countries, Kaggle hosts contests organized by the companies for which contestants try to build the best prediction models. Since its establishment in 2010, Kaggle has served all kinds of organizations from small and medium enterprises (SMEs) to multinational corporation (MNCs) like GE, Allstate, Ford, and Facebook.

4.1 Data Collection

Kaggle maintains and updates the raw meta data about each contest, which can be downloaded from the website directly. This study collected observations on qualified Kaggle's public contests from its launch in April 2010 through September 2020. The monetary reward for the winning team in a contest varied between 0 and $500,000. To obtain more meaningful insights, this study only includes the contests that offer at least $250. Each team to be included in statistical analyses must comprise two or more members (i.e., single-member teams are excluded), at least one of whom should have some previous contest experiences. The final sample comprises 9,793 teams participating in 246 contests. The unit of analysis is submission, and each record is a tentative or final solution submitted by a team for a contest.

Based on the Contests, Organizers, Submissions, Teams, and Users tables obtained from Kaggle's website portal, this study extracted the information needed and aggregated the records into one file. Table II summarizes the operationalization of dependent variable and independent variables. Among them, some remain the same as in the raw data, including team performance, team size, and all the contest-related variables. The remaining are calculated with the original information using R. Based on the Submissions table, for instance, Boundary Spanning is the count of submissions made by each team for a contest.

Table II. Variable Operationalization

Variable	Operationalization
<u>Dependent</u>	
Boundary Spanning	Number of submissions that a team made in a contest by the deadline
Team Performance	Final contest score that a team received
<u>Explanatory</u>	
Network Closure	Total number of times that team members have teamed up with each other
Previous Contest Performance	Average of contest score that each member's last team received
Boundary Spanning Experience	Average normalized difference between preliminary ranking and final ranking of each member's last team in a previous contest
<u>Contest-related Control</u>	
Total Reward	Total monetary reward that a contest offers
Number of Prizes	Number of prizes for a contest
Number of Competitors	Number of competitors for a contest
Contest Duration	Contest duration in number of days
<u>Team-related Control</u>	
Team Tenure	Average time elapsed since each team member joined the platform
Team Size	Number of members in the team
Team Seasonedness	Average number of contests that team members previously attended

Compared with the mediating Boundary Spanning, Team Performance is the eventual outcome measured by the final score that a team receives for each contest. Kaggle calculates performance score based on how well a team does in a contest, the number of members on the team, and the number of teams in the contest[1]:

$$\left[\frac{100000}{\sqrt{N_{teammates}}}\right][Rank^{-0.75}][\log_{10}(1+\log_{10} N_{teams}))][e^{\frac{-t}{500}}], \qquad (1)$$

where *t* is the number of days elapsed since the time when points were awarded. At the cutoff of each calculation, *t* typically takes the value of zero. For example, a team has four team members, ranked 25th in the current contest, and there are 100 teams participated in this contest. The performance score that this team receives is:

$$\left[\frac{100000}{\sqrt{4}}\right][25^{-0.75}][\log_{10}(1+\log_{10} 100))][e^{\frac{0}{500}}] = 2133.7 \qquad (2)$$

Also known as "team ties", Network Closure is measured as the number of times that a team's members have worked with each other before the current contest (Dissanayake, Zhang, and Gu 2015). As each member has worked with others at different frequencies, the whole team's network closure is the sum of collaborations among all its members in previous contests. For example, users

[1] https://www.kaggle.com/progression

A, B and C are members of a team in a current contest. Previously, A and B have collaborated twice, B and C have collaborated three times, and A and C have never collaborated. The network closure is 2+3+0 = 5. As the main-effect variable, Network Closure captures the aggregate asset of internal collaborative relationships. Its effect will be controlled by team size in statistical analyses.

Previous Contest Performance is operationalized as the average of performance scores that relevant members' last teams made. If a member never participated in any teams before, the value is blank and excluded from the calculation. For example, a team comprises one novice member and two experienced members: one's last team scored 15 in a previous contest and the other's scored 17. The current team's previous contest performance is (15+17)/2 = 16.

Meanwhile, Boundary Spanning Experience is the average normalized difference between the initial ranking and the final ranking of each member's last team. Though tentative and formal solutions are evaluated with different datasets, the change in rankings still gives team members a clear hint of how helpful boundary spanning (i.e., submitting tentative solutions and receiving feedback from the platform before the deadline) is to their collective endeavor. In the above team, for instance, one veteran member's last team ranked 5^{th} eventually but 8^{th} initially among 30 teams, and the other member's last team ranked 6^{th} eventually but 7^{th} initially among 20 teams, leading to the average normalized rank difference of [(8-5)/30+(7-6)/20]/2 = 0.075.

To control for team and contest heterogeneity in an effort of mitigating possible analysis biases, this study includes seven control variables. The first two control for total prize number and reward amount of each contest, as monetary incentive is an important factor affecting individual performance in crowdsourcing contests (Archak 2010). The third concerns the number of competitors: how many teams competing with each other in a specific contest affects participants' probability of winning (Archak 2010). The fourth pertains to contest duration, as it takes time for team members to know and work with each other. Next, Team Tenure captures the average number of days between each member's registration date on the platform and the start date of the current contest. People of longer tenure tend to have better performance in crowdsourcing contests (Javadi Khasraghi and Hirschheim 2021). The sixth variable controls for team size: the number of members affects individuals' participation in crowdsourcing contests (Yang, Chen, and Pavlou 2009). Finally, Team Seasonedness measures the average number of previous contests that each member has attended, because previous experience is identified as one important factor affecting crowdsourcing contest performance (Javadi Khasraghi and Aghaie 2014).

4.2 Descriptive and Correlation Analyses

Table III gives the descriptive statistics of all independent, dependent, and control variables. The profiles of participating teams in crowdsourcing contests vary greatly. Some variables also exhibited relatively large skewness, suggesting the need to normalize them in further analyses. Specifically, this study applies log transformations on Team Performance, Previous Contest Performance, Total Reward, Total Competitors, and Team Tenure. By making their distributions less skewed, the transformations ensure that the assumptions of inferential statistics are met.

Table III. Descriptive Statistics

Variable	Minimum	Maximum	Mean	Std. Deviation
Boundary Spanning	1.00	671.00	55.56	78.21
Team Performance	42.32	49082.37	2055.43	4614.73
Network Closure	0.00	472.00	2.86	8.95
Previous Contest Performance	11.11	46838.39	1717.80	3527.07
Boundary Spanning Experience	-0.98	0.98	0.00	0.13
Total Reward	250.00	1500000.00	72998.89	181367.57
Number of Prizes	0.00	13.00	3.82	1.73
Total Competitors	24.00	8802.00	2369.92	1945.61
Contest Duration	22.00	731.00	88.70	49.16
Team Tenure	2.78	2746.00	344.16	325.35
Team Size	2.00	40.00	2.92	1.53
Team Seasonedness	0.03	49.50	2.65	4.06

Table IV reports the correlation and collinearity among independent and control variables. The highest correlation coefficient was 0.59, which is between team tenure and team seasonedness. Though the other correlation coefficients were relatively small, their potential multicollinearity is examined as well. The variance inflation factor (VIF) of each variable obtained with OLS regression was less than 2, dismissing most of the multicollinearity concern.

Table IV. Correlation Matrix and Collinearity Statistics

Variable	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]

[1]	Network Closure	1.39									
[2]	Previous Contest Performance (log)	0.04	1.34								
[3]	Boundary Spanning Experience	0.00	-0.21	1.06							
[4]	Total Reward (log)	-0.03	-0.09	0.01	1.54						
[5]	Number of Prizes	0.00	-0.09	-0.09	0.32	1.16					
[6]	Total Competitors (log)	-0.04	-0.24	0.02	0.38	0.09	1.23				
[7]	Contest Duration	0.01	-0.02	-0.02	0.37	0.02	0.04	1.20			
[8]	Team Tenure (log)	0.10	0.37	-0.06	0.06	0.03	-0.01	0.08	1.71		
[9]	Team Size	0.44	-0.06	0.00	0.01	0.04	0.00	0.02	-0.16	1.31	
[10]	Team Seasonedness	0.22	0.31	-0.05	-0.01	0.01	0.00	-0.01	0.59	-0.06	1.63

Note: On the diagonal of the correlation matrix are variation inflation factors (VIFs).

5. Analysis and Results

Operationalized as the number of submissions made by a team for a contest, boundary spanning is a discrete variable. The descriptive statistics indicate that its variance was higher than its mean, leading to the overdispersion concern. To address this issue regarding boundary spanning as the dependent variable, this study employs negative binomial regression modeling in the first-stage analysis. Widely used in the settings of information systems, negative binomial regression modeling mitigates overdispersion with the Poisson-Gamma mixture approach (K. Boudreau et al. 2012; K. J. Boudreau, Lacetera, and Lakhani 2011; Fullerton et al. 1999). In the second-stage analysis, team performance is the dependent variable. It is a continuous variable with high skewness, and log transformation is applied before linear regression to make sure that all the assumptions are met. In addition, control variables take care of extraneous influences at contest and team levels.

There are three statistical models specified for different purposes. Whereas Model 1 and Model 2 cover both stages to predict Boundary Spanning as well as Team Performance, Model 3 only predicts Team Performance at the second stage. Due to the log transformation of Team Performance, the linear regression model predicting it has the same predictor layout with the negative binomial model predicting Boundary Spanning in Models 1 and 2. Model 1 presents the direct impacts of Team Network Closure and other two main explanatory variables (i.e., Previous Contest Performance and Boundary Spanning Experience) as well as contest-related and team-related control variables.

Model 1:

Boundary Spanning/Team Performance

$$
\begin{aligned}
= Exp(C + \ & \beta_1 * \textit{Team Network Closure} \\
& + \beta_2 * \textit{ln (Previous Contest Performance)} \\
& + \beta_3 * \textit{Boundary Spanning Experience} \\
& + \beta_4 * Total\ Reward \\
& + \beta_5 * Number\ of\ Prizes \\
& + \beta_6 * \ln (Total\ Competitors) \\
& + \beta_7 * Competition\ Duration \\
& + \beta_8 * \ln (Team\ tenure) \\
& + \beta_9 * Team\ Size \\
& + \beta_{10} * Team\ Seasonedness \\
& + \in)
\end{aligned}
$$

Model 2 examines the interaction effects of Team Network Closure with the other two main explanatory variables that capture existing team conditions. Thus, the two interaction terms between Team Network Closure and Previous Contest Performance as well as Boundary Spanning Experience are included.

Model 2:

Boundary Spanning/Team Performance

$$
\begin{aligned}
= Exp(C + \ & \beta_1 * \textit{Team Network Closure} \\
& + \beta_2 * \textit{ln (Previous Contest Performance)} \\
& + \beta_3 * \textit{Boundary Spanning Experience} \\
& + \beta_4 * Total\ Reward \\
& + \beta_5 * Number\ of\ Prizes \\
& + \beta_6 * \ln (Total\ competitors) \\
& + \beta_7 * Competiton\ Duration \\
& + \beta_8 * \ln (Team\ tenure) \\
& + \beta_9 * Team\ Size \\
& + \beta_{10} * Team\ Seasonedness \\
& + \beta_{11} * \textit{Network Closure} \times \\
& \qquad \ln (Previous\ performance\ of\ Team\ Members) \\
& + \beta_{12} * \textit{Network Closure} \times \\
& \qquad Previous\ experience\ with\ Boundary\ Spanning
\end{aligned}
$$

$+ \in)$

Model 3 assesses the mediating effect of Boundary Spanning between Team Network Closure and Team Performance. There are three variations: Model 3A is the full model, Model 3B constrains the coefficient of Boundary Spanning to be 0, and Model 3C constrains the coefficient of Team Network Closure to be 0.

Model 3:

$$
\begin{aligned}
\textit{Team Performance} \\
= Exp(C + \ & \beta_1 * \textit{Team Network Closure} \\
& + \beta_2 * \textit{Boundary Spanning} \\
& + \beta_3 * \textit{ln (Previous Contest Performance)} \\
& + \beta_4 * \textit{Boundary Spanning Experience} \\
& + \beta_5 * \textit{Total Reward} \\
& + \beta_6 * \textit{Number of Prizes} \\
& + \beta_7 * ln\ (\textit{Total Competitors}) \\
& + \beta_8 * \textit{Competition Duration} \\
& + \beta_9 * ln\ (\textit{Team tenure}) \\
& + \beta_{10} * \textit{Team Size} \\
& + \beta_{11} * \textit{Team Seasonedness} \\
& + \in)
\end{aligned}
$$

Table V reports the results of the negative binomial model that predicts Boundary Spanning in first-stage analysis. Hypothesis 2 was supported at the 0.01 level, suggesting that Team Network Closure has a significant negative effect on Boundary Spanning. Hypothesis 4 was also supported at the 0.01 level, suggesting that Previous Contest Performance moderates the relationship between Team Network Closure and Boundary Spanning. There was not enough evidence for Hypothesis 6 regarding the moderating effect of Boundary Spanning Experience on the relationship between Team Network Closure and Boundary Spanning. As for the control variables, the results showed the significant effects (*p*-values less than 0.05) of Total Reward, Number of Prizes, Number of Competitors, Team Tenure, Team Size, and Team Seasonedness. Contest Duration was marginally significant at the 0.1 level.

Table V. Negative Binomial Model Predicting Boundary Spanning

Predictor	Model 1	Model 2
Network Closure	-0.012 (125.395) ***	-0.011 (67.981) ***
Previous Contest Performance (log)	0.321 (777.137) ***	0.331 (795.987) ***
Boundary Spanning Experience	0.449 (25.573) ***	0.395 (12.217) ***
Total Reward (log)	-0.073 (21.907) ***	-0.073 (22.077) ***
Number of Prizes	-0.151 (287.510) ***	-0.151 (286.389) ***
Number of Competitors (log)	0.470 (803.183) ***	0.473 (810.065) ***
Contest Duration	0.0001 (3.266) *	0.0001 (3.394) *
Team Tenure (log)	0.137 (39.748) **	0.137 (39.519) **
Team Size	0.298 (698.427) ***	0.302 (707.876) ***
Team Seasonedness	0.018 (17.428) ***	0.018 (17.993) ***
Network Closure × Previous Contest Performance		-0.011 (21.840) ***
Network Closure × Boundary Spanning Experience		0.017 (0.818)

Note: Chi-square statistic (χ^2) given in the paratheses beside each coefficient estimate. * - significance at the 0.1 level; ** - significance at the 0.05 level; *** - significance at the 0.001 level

Table VI reports the results of the linear regression model that predicts Team Performance in second-stage analysis. Hypothesis 3 was supported at the 0.01 significance level, suggesting that Team Network Closure has a significant negative effect on Team Performance. There was not enough evidence for Hypothesis 5 regarding the moderating effect of Previous Contest Performance on the relationship between Team Network Closure and Team Performance. Hypothesis 7 was not supported either regarding the moderating effect of Boundary Spanning Experience on the relationship between Team Network Closure and Team Performance. Nevertheless, the direct effects of Previous Contest Performance and Boundary Spanning Experience on Team Performance were significant. As for control variables, the results showed the significant effects of Number of Competitors, Team Tenure, Contest Duration, and Team Seasonedness. However, Total Reward and Number of Prizes were not found impactful on Team Performance.

Table VI. Regression Model Predicting Ln(Team Performance) without Boundary Spanning

Predictor	Model 1	Model 2
Network Closure	-0.008 (-6.20)***	-0.009 (-5.71)***
Previous Contest Performance (log)	0.412 (37.10)***	0.411 (35.52)***
Boundary Spanning Experience	0.667 (7.67)***	0.613 (5.40)***
Total Reward (log)	-0.014 (-0.97)	-0.014 (-0.98)

Number of Prizes	-0.006 (-0.76)	-0.006 (-0.78)
Number of Competitors (log)	-0.445 (-29.40)***	-0.444 (-29.35)***
Contest Duration	-0.001 (-3.17)***	-0.001 (-3.17)***
Team Tenure (log)	0.161 (7.96)***	0.161 (7.96)***
Team Size	0.099 (11.03)***	0.099 (11.00)***
Team Seasonedness	0.024 (6.31)***	0.024 (6.31)***
Network Closure × Previous Contest Performance		0.001 (0.35)
Network Closure × Boundary Spanning Experience		0.013 (0.74)

Note: Critical value (*t*) given in the paratheses beside each coefficient estimate. * - significance at the 0.1 level; ** - significance at the 0.05 level; *** - significance at the 0.001 level

Table VII reports the results of the linear regression model including Boundary Spanning to predict Team Performance. Models 3A, 3B and 3C suggest that Team Network Closure and Boundary Spanning had significant effects on Team Performance together as well as separately. As expected, the results supported Hypothesis 1 that Boundary Spanning has a positive impact on Team Performance. Together with supported Hypotheses 2 and 3, the findings suggest that Boundary Spanning plays the role of partial mediator between Team Network Closure and Team Performance. In addition, the presence of Boundary Spanning reduced the negative effect of Team Network Closure by half (from -0.008 to -0.004). Thus, reaching out for platform feedback is indeed an effective approach to "break" network closure.

Table VII. Regression Model Predicting Ln (Team Performance) with Boundary Spanning

Predictor	Model 3A	Model 3B	Model 3C
Network Closure	-0.004 (37.40)***	-0.008 (-6.20)***	
Boundary Spanning	0.006 (-2.93)***		0.006 (37.90)***
Previous Contest Performance (log)	0.293 (27.95)***	0.412 (37.10)***	0.293 (27.94)***
Boundary Spanning Experience	0.520 (6.637)***	0.667 (7.67)***	0.517 (6.59)***
Total Reward (log)	0.008 (0.63)	-0.014 (-0.97)	0.009 (0.73)
Number of Prizes	0.026 (3.57)***	-0.006 (-0.76)	0.026 (3.65)***
Number of Competitors (log)	-0.595 (-41.93)***	-0.445 (-29.40)***	-0.595 (-41.91)***
Contest Duration	-0.001 (-3.85)***	-0.001 (-3.17)***	-0.001 (-3.89)***
Team Tenure (log)	0.112 (6.16)***	0.161 (7.96)***	0.110 (6.01)***
Team Size	-0.009 (-0.99)	0.099 (11.03)***	-0.020 (-2.66)***
Team Seasonedness	0.017 (4.86)***	0.024 (6.31)***	0.014 (4.35)***

Note: Critical value (*t*) given in the paratheses beside each coefficient estimate. * - significance at the 0.1 level; ** - significance at the 0.05 level; *** - significance at the 0.001 level

6. Robustness Checks

This section further examines the robustness of statistical results, both conceptually and empirically. The primary concern is the potential endogeneity issue that threatens the causality in identified relationships. Compared with cross-sectional analyses, longitudinal analyses are more capable of avoiding the reverse relationships caused the endogeneity issue. Though this study does not use time-lag data explicitly, the way it collected observations follows the same principle. Each team was formed before it started to make any submissions, and team performance could only be measured after all the teams made their submissions by the deadline. This mitigate the possibility that there are reverse relationships from team network closure to boundary spanning, from team network closure to team performance, and from boundary spanning to team performance.

To validate the findings empirically, further analyses employ alternative methods and measures. If the empirical results are largely consistent in terms of coefficient signs and significance levels, there is support for the robustness of main findings. First, the intermediate dependent variable, Boundary Spanning, is treated as an ordinal variable in an ordered logistic regression analysis. The results shown in Table VIII were consistent with the previous findings.

Table VIII. Ordinal Logistic Regression Model Predicting Boundary Spanning

Predictor	Model 1	Model 2
Team Network Closure	-0.016***	-0.015***
Previous Contest Performance (log)	0.534***	0.541***
Boundary Spanning Experience	0.866***	0.781***
Price (log)	-0.157***	-0.157***
Number of Prizes	-0.215***	-0.215***
Total Competitors (log)	0.753***	0.754***
Contest Duration	-0.003***	-0.003***
Team Tenure (log)	0.133**	0.132**
Team Size	0.374***	0.374***
Team Seasonedness	0.040***	0.040***
Network Closure × Previous Contest Performance		-0.007***
Network Closure × Boundary Spanning Experience		0.022

Note: * - significance at the 0.1 level; ** - significance at the 0.05 level; *** - significance at the 0.001 level

As for the eventual outcome, Team Performance, it is measured differently for model estimation. The performance score are obtained with random 30% test datasets, rather than the rest used for final score calculation. The substitution of team performance with alternative score brought ignorable changes to the results, as shown in Table IX.

Table IX. Linear Regression Model Predicting ln (Alternative Score)

Predictor	Model 1	Model 2
Team Network closure	-0.009***	-0.009***
Previous Contest Performance (log)	0.407***	0.407***
Boundary Spanning Experience	-0.621***	-0.610***
Total Reward (log)	0.011	0.011
Number of Prizes	-0.092***	-0.092***
Number of Competitors (log)	-0.388***	-0.388***
Contest Duration	-0.001***	-0.001***
Team Tenure (log)	0.123***	0.123***
Team Size	0.101***	0.101***
Team Seasonedness	0.022***	0.022***
Network closure × Previous Contest Performance		0.002
Network Closure × Boundary Spanning Experience		-0.002

Note: * - significance at the 0.1 level; ** - significance at the 0.05 level; *** - significance at the 0.001 level

Last, the previous analyses used all team members in the calculation of historical variables including Previous Contest Performance and Boundary Spanning Experience. To check whether the exclusion of "inexperienced" team members affects the results or not, this section only considers the team members who had participated in at least one contest before in the calculation. Table X reports the results based on the observations concerning experienced team members only, which were consistent with those based on all.

Table X. Results Based on Experienced Team Members

Predictor	Boundary Spanning		Team Performance	
Network Closure	-0.010***	-0.008***	-0.005***	-0.005***
Previous Contest Performance (log)	0.344***	0.356***	0.430***	0.431***
Boundary Spanning Experience	0.446***	0.385***	0.638***	0.574***
Total Reward (log)	-0.078***	-0.078***	-0.018	-0.018
Number of Prizes	-0.151***	-0.151***	-0.007	-0.007

Number of Competitors (log)	0.481**	0.484***	-0.437***	-0.437***
Contest Duration	-0.001***	-0.001*	-0.001*	-0.001***
Team Tenure (log)	0.174***	0.175***	0.198**	0.197**
Team Size	0.255***	0.257***	0.050***	0.050***
Team Seasonedness	0.016***	0.016***	0.022***	0.022***
Network Closure × Previous Contest Performance		-0.011***		-0.001
Network Closure × Boundary Spanning Experience		0.020		0.016

Note: Under each dependent variable, the left column gives Model 1 estimates, and the right column gives Model 2 estimates. * - significance at the 0.1 level; ** - significance at the 0.05 level; *** - significance at the 0.001 level

The robustness check results demonstrate consistency with the original, and confirm main findings. As reported in Table XI, all the main effects involved in the mediating relationships among Team Network Closure, Boundary Spanning, and Team Performance are supported as hypothesized. This suggests that Boundary Spanning is indeed a partial mediator between Team Network Closure and Team Performance. Among the four moderating relationships, there is evidence for one of them. Nevertheless, the direct effects of historical variables (i.e., Previous Contest Performance and Boundary Spanning Experience) on present variables (i.e., Team Performance and Boundary Spanning) are strong as expected. As for Previous Contest Performance, the results suggest that it reduces the negative effect of Team Network Closure on Boundary Spanning, but not that on Team Performance. Meanwhile, Boundary Spanning Experience is not a salient moderator in either case.

Table XI. Summary of Hypothesis Testing

Hypothesized Relationship	Supported
H1: Main effect of Boundary Spanning on Team Performance	Yes
H2: Main effect of Team Network Closure on Boundary Spanning	Yes
H3: Main effect of Team Network Closure on Team Performance	Yes
H4: Moderating effect of Previous Contest Performance on path H2	Yes
H5: Moderating effect of Previous Contest Performance on path H3	No
H6: Moderating effect of Boundary Spanning Experience on path H2	No
H7: Moderating effect of Boundary Spanning Experience on path H3	No

7. Discussions

The results reveal how team network closure affects boundary spanning behavior and team performance in crowdsourcing contests. At a higher level of network closure, boundary spanning activities decrease, leading to lower team performance. These results are consistent with the theoretical strand of social capital claiming that network closure “closes up” structural holes, reducing the need for information outreach. In the positive sense, network closure increases access to internal knowledge as team members work more closely with each other (Dissanayake, Zhang, and Gu 2015). In the negative sense, network closure compromises decision quality due to information exchange redundancy within a team (Lee, Bachrach, and Lewis 2014). In the crowdsourcing context, the findings of this study suggest that team network closure helps a team get into a groove quickly, yet preventing members to think outside the box.

Unlike a typical mediator that has positive relationships with both antecedent and outcome variables, boundary spanning is found to have a negative relationship with team network closure but a positive relationship with team performance. Thus, boundary spanning is not a regular “facilitating condition” but rather a “cycle breaker”. As a “countermeasure” to network closure, platform feedback encourages team members to reach out for information. Therefore, making tentative submissions for preliminary feedback is indeed helpful for the enhancement of team performance. This is consistent with the simulation results in a previous study that platform feedback helps contest teams improve crowdsourcing outcome (Jiang, Huang, and Beil 2021).

The only significant moderating relationship suggests that the negative effect of network closure on boundary spanning is stronger for the teams that have higher previous contest performance. A project team with a lot of knowledge has positive judgement of its capability, obviating the need for seeking new information (Haas and Hansen 2005). In crowdsourcing contests, similarly, team members in fresh memory of prior success are demotivated to reach out for platform feedback but rely on their own resources.

Meanwhile, there is not sufficient evidence for the moderating effect of boundary spanning experience on the relationship between network closure and boundary spanning. In Kaggle contests, team membership is fluid from one contest to another. Even if every member has positive boundary spanning experience before, they do not share a collective memory but have to explore the timing and frequency of such a practice in the current contest. Nevertheless, the sign of coefficient associated with the interaction term is positive as expected, suggesting a possibility for prior boundary spanning experience to mitigate the negative impact of network closure.

As for the relationship between team network closure and team performance, the hypothesized negative effect is confirmed. Teams that rely on internal knowledge rather than external feedback have lower performance. This confirms that the presence of network closure within a team raises the level of exchange redundancy that is counterproductive (Burt 2009). Little support was found on the moderating effect of either previous contest performance or boundary spanning experience on the relationship between network closure and team performance. Compared with boundary spanning that pertains to the number of submissions, team performance is more closely related to both historical variables in terms of construct operationalization as they are all based on the ranking of submissions. As the two historical variables are more like "time-lagged" observations to current team performance, their direct effects on the latter were very strong, suppressing their potential moderating effects.

8. Conclusion and implications

Based on the objective observations collected from Kaggle, an influential crowdsoucing platform that provides feedback to tentative sulutions, this study examines the relationships among network closure, boundary spanning and team performance under the moderation of previous contest performance and boundary spanning experience. The empirical results confirm that network closure has negative impacts on boundary spanning and team performance. Furthermore, there is supporting evidence that boundary spanning plays the role of partial and negative mediator between network closure and team Performance. Regarding the difference made by historical variables, it is found that previous contest performance reduces the negative effect of network closure on boundary spanning.

This study has limitations that point to furture research directions. First, the findings are based on the observations concerning one crowdsourcing platform, and may not be generalizable to other platforms. This calls for more research on network closure and boundary spanning on multiple crowdsourcing platforms for different types of projects. Second, this study only used public-release data from Kaggle platform, which limit variable availability and operationalization. Future research can capture members' perspectives on boundary spanning to get an in-depth understanding of the factors that promote information outreach. Such subjective observations collected with methods like survey and interview may reveal what actually encourage and inhibit boundary spanning, and how its timing and frequency affect team functioning.

Despite these limitations, the findings contribute to the literature and practice. This study offers a coherent lens that accounts for the dyanmics among network closure, boundary spanning, and team performance in crowdsourcing contests. The insights help developers and managers improve platform design and facilitate member participation.

8.1 Theoretical implications

Network closure is a double-edged sword: the close bond among members is conducive to team cohesiveness, but may also lure them into a false sense of self-sufficiency. In the context of crowdsourcing, the critical question is: how does network closure affect team boundary spanning and team performance? This study addresses this research question with team- and member-level data from Kaggle.com. As a well-known crowdsourcing contest platform, Kaggle facilitates boundary spanning for team members, especially by providing feedback to their tentative solutions submitted before deadlines.

The different ways that boundary spanning and team performance are operationalized (discrete count vs. continuous score) demand distinct modeling approaches when each is used as the dependent variable. Meanwhile, team- and contest-related variables control for the effects of team network closure as the predictor and boundary spanning as the mediator. The ad-hoc nature of contest teams implies that their capabilities for boundary spanning and team performance depend on individual members' relevant experiences in their previous teams. The panel data allows the examination of how team network closure impacts two dependent variables under the influence of pre-existing conditions as moderators. The results support the mediator role played by boundary spanning between network closure and team performance, and the moderator role played by previous contest performance on the relationship between network closure and boundary spanning.

The findings extend the literature of network closure and boundary spanning to the context of crowdsourcing contest platforms. Prior studies focus on network closure effect in various non-competitive settings, such as startup bootcamps and entrepreneurial teams. When performance is evaluated independently among teams, network closure instills a sense of potency within each (Hasan and Koning 2019; Ruef 2002). In competitive settings, stronger network closure demotivates boundary spanning; rather, team members rely mainly on internal resources for task accomplishment.

One theoretical strand of social capital posits the essence of structural holes. In the context of crowdsourcing contests, this study demonstrates that the presence of network closure builds up information exchange redundancy but boundary spanning helps diminish it. Therefore, a team of stronger network closure often ends up with lower contest achievement. In addition, the success in prior contests may strengthen the negative effect of network closure on boundary spanning as team members tend to be self-complacent. Meanwhile, if team members found it helpful to reach out for information in previous contests, they are more likely to engage in boundary spanning for the current contest. This is supported with the strong direct effect of boundary spanning experience on boundary spanning, though its moderating effect on the relationship between network closure and boundary spanning is relatively weak.

8.2 Practical implications

The findings yield insights for optimal design of crowdsourcing contest platforms to promote boundary spanning and team performance. To reduce the negative impact of network closure, certain mechanisms should be in place encouraging users to team up with those they do not have the chance to work together previously. For instance, the algorithm of performance score calculation may take network closure into account and reward relatively “open” teams with bonus points.

More importantly, a platform needs to promote the boundary spanning activities of all teams. In addition to the provision of feedback to tentative solutions submitted by teams before a contest ends, crowdsourcing platforms may facilitate information outreach in other forms. For example, help desk and expert consultation make informational resources more accessible to platform users (Bigliardi, Ivo Dormio, and Galati 2012; Marrone 2010; Van Osch and Steinfield 2018).

Through the measures that diminish network closure and promote boundary spanning, platform facilitations help teams to enhance skills and improve solutions in crowdsourcing contests. Crowdsourcing sponsors may also come up with various incentives for encouraging members to act beyond their confort zone. In this manner, team creactivity and productivity will be maximized.

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