HOW DO DIFFERENT NETWORK POSITIONS AFFECT CROWD MEMBERS' SUCCESS IN CROWDSOURCING CHALLENGES?

Erica Mazzola, Mariangela Piazza, Giovanni Perrone
Università degli Studi di Palermo, Dipartimento di Ingegneria

ABSTRACT

Within online communities, participants can interact with each other and socialize by, for example, chatting, exchanging feedback, providing advice, discussing, and commenting on ideas. These social interactions shape a community network, that is a set of social relationships developed by community members. This study aims at investigating how occupying diverse network positions within a specific kind of online community, a crowdsourcing community, increases the members' likelihood to succeed in a competition. Drawing on social capital literature, we hypothesize how occupying central and structural hole network positions can increase the solvers' chances of winning crowdsourcing contests. To empirically test the developed hypotheses, we built a crowdsourcing community network shaped by 2479 solvers within the community of the 99designs crowdsourcing platform. In terms of the number of won contests, we found that both occupying a central position and assuming a structural hole network position within the crowdsourcing community network showed an inverted U-shaped effect on the success of solvers. The results of this study contribute to previous crowdsourcing literature and provide critical implications for online community members and managers organizing competition among their members.

Keywords: Crowdsourcing, solvers' success, online community network, structural network embeddedness

INTRODUCTION

Since allowing a large group of people to exchange knowledge and information, online communities (e.g., open source, social networks, users, and crowdsourcing communities) represent "great good places" to promote innovation (Becker et al. 2021; Safadi, Johnson, and Faraj 2021). Among others, crowdsourcing communities have increasingly gained popularity as a channel of innovation for organizations (i.e., seekers) aiming to access valuable knowledge and creative ideas from a large and undefined pool of community members (i.e., solvers) (Garcia Martinez 2015; Mazzola et al. 2018).

There is a growing consensus in the literature regarding investigation of online communities as networks shaped by social relationships among community members that interact with each other to exchange knowledge and information (Ganley and Lampe 2009; Faraj and Johnson 2011a; Faraj et al. 2016). In the crowdsourcing context, the community network is made up of social relationships among solvers that exchange feedback, provide advice, discuss their ideas and evaluate their solutions through mechanisms such as chatting, posting and commenting (Freeman 1991; Chan, Li, and Zhu 2015; Renard and Davis 2019).

Previous research addressing online communities as networks have favored a structural network embeddedness perspective, suggesting how members of a community occupy specific positions that influence their knowledge exchange and information access (Faraj et al. 2016). Considering this perspective, previous scholars have mainly focused on online communities where members collaborate in the pursuit of common interests, such as to sustain open-source projects (e.g., open source software and hardware communities), share content (e.g., social networks), develop collective knowledge (e.g., wikis and question and answer websites), and develop new ideas supporting user interactions (e.g., user communities) (Zhang and Wang 2012; Hwang, Singh, and Argote 2019; Maruping, Daniel, and Cataldo 2019; Resch and Kock 2021; Safadi, Johnson, and Faraj 2021). However, so far, previous scholars have disregarded the structural network embeddedness perspective when investigating the primary issues in crowdsourcing communities. A quite recent exception is the study by Ozaygen and Balagué (2018), which shows how solvers' positioning in a crowdsourcing community network influences their ideas evaluations.

We reason that taking a structural network perspective is also particularly relevant in communities of a competitive nature, where members can leverage their network positions to improve their success (Gulati, Nohria, and Zaheer 2000). In the crowdsourcing communities, a fierce competition characterises the interactions among solvers, thereby leading to challenging each other in the development of the best solution proposal to emerge from the crowd and win the competition (Natalicchio, Messeni Petruzzelli, and Garavelli 2014; Piazza, Mazzola, and Perrone 2022). In this peculiar scenario, solvers can take advantage of acquiring critical knowledge and information from the community and exploiting them to develop innovative ideas and creative proposals (Garcia Martinez 2017). There is an ongoing conversation in the online community literature about favorable network structures for information advantages, suggesting how assuming specific positions within the community network allows members to access valuable knowledge and develop innovative and creative ideas (Faraj et al. 2016; Resch and Kock 2021; Safadi, Johnson, and Faraj 2021). For example, community members can have an edge over their peers by establishing network closure structures (i.e., highly dense structures where members' direct contacts establish relationships with each other), whereby generating trust among members facilitates collaboration and allows the transfer of tacit knowledge (Perry-Smith and Manucci 2017). Thus, adopting a structural network embeddedness perspective to investigate the crowdsourcing community network may be beneficial to understand how solvers face the competition and succeed in a contest, by occupying different positions within the network.

Leveraging prior literature on networks and online communities (Burt 2001; Koka and Prescott 2002; Zhang and Wang 2012; Maruping, Daniel, and Cataldo 2019; Wang et al. 2020), we aim to investigate how occupying specific network positions within the crowdsourcing community network increases the solvers' likelihood to succeed. Following such literature, we theorise how central and structural hole network positions influence the solvers' likelihood of winning crowdsourcing contests by leveraging the knowledge and information flows that they can access through such network positions. Particularly, considering the inherent advantages and drawbacks associated with both centrality and structural hole positions, we hypothesize that these network positions have a curvilinear (inverted U-shape) effect on the solvers' likelihood to win crowdsourcing contests. Empirically we built an ad-hoc dataset considering the 99designs crowdsourcing community, and gathered secondary data from a sample of 2479 solvers. Screening the solvers' profiles, we collected data about their skills and capabilities and information about their success within the 99designs crowdsourcing community. Moreover, considering the blog of the 99designs crowdsourcing community, we retrieved information about the solvers' social interactions to construct the crowdsourcing community network. Finally, we performed an econometric analysis and found that occupying a central or a structural hole position when engaging in social interaction with peers does indeed have an inverted U-shape effect on the solvers' success in crowdsourcing contests.

The results of this study provide several important theoretical contributions. First, we add to prior literature that have investigated online communities as networks (Özaygen and Balagué 2018; Wang et al. 2020; Becker et al. 2021; Resch and Kock 2021) by highlighting how adopting a structural network embeddedness perspective may be beneficial when also considering competitive online communities to predict members' success. Second, this study contributes to previous crowdsourcing literature investigating the antecedents of the solvers' success (Zhu, Djurjagina, and Leker 2014; Bockstedt, Druehl, and Mishra 2016; Riedl and Seidel 2019) by providing evidence that alongside the already recognized behaviors solvers assume individually, they can also increase their chances of being selected as winners of crowdsourcing contests by leveraging their social interactions with members of the crowdsourcing community. Moreover, this study adds to previous online community literature (e.g., Shen, Lee and Cheung, 2014; Faullant and Dolfus, 2017; Hwang, Singh and Argote, 2019; Renard and Davis, 2019) by highlighting that social interactions in crowdsourcing communities have diverse (positive and negative) effects on solvers' success, according to the network structure shaped by such social interactions. Finally, the results of this research offer also important practical implications for online community members and managers organizing competition among their community members by suggesting to them how to manage social interactions within crowdsourcing communities.

HYPOTHESES DEVELOPMENT

Structural network embeddedness is defined as the configuration of linkages between network actors, and it particularly describes the presence or absence of such links and the overall structure of network connections (Granovetter, 1992). We followed prior network theories and considered centrality and structural holes network positions as the two main dimensions of analysis, when considering a structural network embeddedness perspective (Borgatti, Everett, and Freeman 2002; Koka and Prescott 2008). Scholars associate centrality and structural holes with the extent of information and knowledge that actors can obtain from their network of relationships, and both positions have inherent advantages and drawbacks that must be considered (Koka and Prescott 2002; Moran 2005; Koka and Prescott 2008). In the following sections, we discuss how assuming central and structural holes network positions in the crowdsourcing community network impacts the solvers' success in crowdsourcing contests.

Centrality

A central network position in a crowdsourcing community network occurs when solvers interact with a high number of solvers, or because they establish ties with many solvers who themselves interact with many others (Koka and Prescott 2008). Because network ties are conduits for resource flows (Galaskiewicz 1979), an actor centrally located in a network benefits from the information volume, i.e., a dimension emphasizing the quantity of information that an actor can access and acquire through its network relationships (Koka and Prescott 2002; Mazzola, Perrone, and Kamuriwo 2015). Occupying a central position in a crowdsourcing community network, solvers can gather a large amount of knowledge and information, such as numerous feedbacks on their solutions and comments about the successes and failures of their peers (Ahuja 2000; Maruping, Daniel, and Cataldo 2019; Renard and Davis 2019).

We argue that occupying a central position within the crowdsourcing community network may be beneficial for the solvers' success. Being exposed to a high volume of information, solvers can improve their capacity of monitoring the external environment to find relevant knowledge and expand their learning opportunities, so increasing their creativity and innovative capabilities (Faraj and Johnson 2011b; Garcia Martinez 2015; Ogink and Dong 2019). Indeed, the accumulation of a high volume of information enhances solvers' capacity to recognize and absorb new knowledge and ideas, as well as their abilities to convert this knowledge into new, creative and innovative solution proposals for crowdsourcing contests (Cohen and Levinthal 1990; Björk and Magnusson 2009; Garcia Martinez 2017). For example, absorbing new knowledge through comments and feedbacks, thanks to the many ties with their peers, and combining it to their existing knowledge base allows solvers to generate inventive solutions resulting from the combination of several pieces of knowledge (Bogers, Foss, and Lyngsie 2018; Riedl and Seidel 2019; Zhu et al. 2019; Ruiz, Brion, and Parmentier 2020). Moreover, centrality also reduces the search costs for finding information able to improve the resolution process of the crowdsourcing contest and succeed in the competition. For instance, being centrally located in the crowdsourcing community network, solvers can more easily discuss with peers who can provide appropriate knowledge and feedback for making the development of the solution proposal successful (Mazzola, Perrone, and Kamuriwo 2015).

However, centrality has also some drawbacks, and we argue that assuming a too central position within the crowdsourcing community network can be detrimental for the solvers' success, because of several reasons. First, solvers that are too centrally located have limited exploration ability, because they do not have access to distant or diverse sources of information (Ahuja 2000). Second, as solvers are limited to proximate searches, a large amount of information processed may be redundant and obsolete (Katila and Ahuja 2002; Koka and Prescott 2002). These circumstances may induce solvers to develop unfounded confidence that they have captured all the relevant knowledge and information needed for developing appropriate solution proposals, leading them to develop poor innovative and creative solutions (Levinthal and March 1993; Koka and Prescott 2002). Additionally, being too centrally located in a crowdsourcing community network may lead solvers to missing the opportunities to interact and communicate with distant solvers who may have diverse ideas (Mazzola, Perrone, and Handfield 2018). This is because interacting with the many and close peers provides a sense of protection from possible opportunistic behaviors and restrains solvers from venturing toward entering into a social relationship with distant solvers (Mazzola, Perrone, and Handfield 2018).

In sum, we argue that occupying a central position in the crowdsourcing community network influences the number of contests won by solvers. Nevertheless, the direction of this relationship depends upon the extent of the centrality reached by solvers. Increasing the number of direct and indirect ties with their peers, and so reaching a position characterized by a low to intermediate level of centrality, allows solvers to gather a high volume of information and absorb new valuable knowledge to develop more creative and innovative solutions, and win crowdsourcing contests. However, as the extent of centrality increases beyond a certain threshold, its benefits on solvers' success are likely to diminish. Since increasing the redundancy of information, limiting the exploration ability, and restraining the willingness to engage in a social relationship with solvers that may provide different and distant knowledge, a too central position reduces the solvers' likelihood to develop more creative and innovative solutions for winning crowdsourcing contests. Thus, considering the above arguments, we hypothesized an inverted U-shape relationship between occupying a central position within the crowdsourcing community network, and the solvers' probability to be selected as the winner of the contest.

Accordingly, we state the first hypothesis of the study.

Hypothesis 1: Having a central position in a crowdsourcing community network has an inverted U-shape effect on the number of contests won by solvers.

Structural hole

A solver occupying structural hole positions in the crowdsourcing community network acts as a bridge between different solvers, otherwise disconnected in the network (Burt 1992; Zaheer and Bell 2005). By relying on the brokerage opportunities created by such an open and not-dense network structure, a structure holes position provides actors with information diversity (Burt 1992; Resch and Kock 2021; Safadi, Johnson, and Faraj 2021). The information diversity dimension emphasizes the variety and, to a somewhat lesser extent, quantity of information and resources that an actor can access from different, and often unconnected groups in the network (Ganley and Lampe 2009). Particularly, solvers that bridge structural holes play a brokering role, and can access comments and feedback from diverse and unconnected peers in the crowdsourcing community network (Fleming and Waguespack 2007).

We reason that occupying a structural hole position within the crowdsourcing community network may be beneficial for the solvers' success. Enabling solvers to access flows of different information from their peers, structural hole positions allow solvers to engage in an exploration activity (Koka and Prescott 2002; Hwang, Singh, and Argote 2019). In accessing different and non-redundant information from diverse parts of the network, solvers can develop new understandings and novel solution proposals, thereby increasing their likelihood to succeed in crowdsourcing contests (Burt 1992; Ahuja 2000; Gilsing et al. 2008; Koka and Prescott 2008). Indeed, gathering information through comments and feedback from unconnected peers with heterogeneous knowledge, solvers occupying a structural hole position can generate more innovative and creative solution proposals, resulting from the recombination of previously unconnected pieces of knowledge (March 1991; Dahlander and Frederiksen 2012).

However, we theorize that assuming a too structural hole position within the crowdsourcing community network can be counterproductive for the solvers' success, because of several reasons. First, structural hole positions limit the exploitative possibilities of the solvers, who dealing with high information diversity, focus exclusively on explorative learning (Levinthal and March 1993). By reducing the exploitative opportunities, the solvers reduce their possibility to establish strong social relationships and acquire in-depth knowledge from their peers, for developing more creative and innovative solution proposals (Koka and Prescott 2002). Moreover, solvers in too structural hole positions tend to commit extensive efforts in assessing the reliability of different information gathered from interacting with diverse peers, so that the limit of their absorptive capacity is quickly reached (Cohen and Levinthal 1990). The lack of absorptive capacity reduces the solvers' possibility to link the new and diverse knowledge, acquired through structural holes positions, with their existing knowledge base, limiting their ability to develop inventive solution proposals for winning crowdsourcing contests (Katila and Ahuja 2002).

As such, we suggest that occupying a structural hole position in the crowdsourcing community network affects the number of contests won by solvers. However, the direction of this relationship depends on the extent of the structural holes reached by solvers. As the solver's position is characterized by low to intermediate level of structural holes, they can benefit from information diversity by absorbing and recombining knowledge from different sources of information, thereby develop more creative and innovative solutions and succeed in crowdsourcing contests. However, as the extent of the structural holes increase and overcome a specific threshold, its benefits on the solvers' possibility of winning crowdsourcing contests are likely to diminish. Since reducing the exploitative learning opportunities, and restraining the possibility to engage in strong relationships with others to acquire in-depth knowledge, a too structural hole position reduces the solvers' likelihood to generate more creative and innovative solutions for winning crowdsourcing contests. Therefore, considering the above argumentations, we hypothesize an inverted U-shape relationship between occupying a structural hole position within the crowdsourcing community network and the solvers' probability to be selected as the winner of the contest.

Accordingly, we state the second hypothesis of the study.

Hypothesis 2: Having a structural hole position in a crowdsourcing community network has an inverted U-shape effect on the number of contests won by solvers.

DATA AND METHODS

Research setting and data collection

To assess the relationships hypothesized, the crowdsourcing community of 99designs, a leading crowdsourcing platform in the online graphic design market that focuses on design problems, was chosen. The contests broadcasted on 99designs are typically related to the designing of logos, business cards, and websites. On the 99designs crowdsourcing platform, challenges are broadcasted through a problem statement describing the seekers' needs and the attributes of the problem to be solved and informing potential solvers about the monetary prize upon success in the competition (Natalicchio, Messeni Petruzzelli, and Garavelli 2017; Mazzola et al. 2020). Solvers screen the problem statements on the platform and decide whether to self-select to participate in the competition by submitting their ideas and designs. Then, the seeker assesses all the ideas received and selects the most creative and innovative as the winning one.

We considered the 99designs crowdsourcing platform as an appropriate setting to investigate how the structural network embeddedness of a crowdsourcing community network influences the solvers' success, for two main reasons. First, 99designs has its discussion blog where solvers can socially interact with each other, chatting, posting and commenting to exchange feedbacks and opinions on the solutions of the other solvers, and share their knowledge and experiences within the community. Thus, it is possible to build a community network shaped by solvers registered on the platform by assessing whether they interact with each other. Second, possible measures of solvers' success, such as the number of contests won, are available on the 99design crowdsourcing platform, which provides solvers with a personal profile web page where they can describe their skills and attitudes, show their capabilities through a design portfolio, and keep track of their achievements (Sun and Grimes 2017; Mazzola et al. 2020).

The solver represents the unit of analysis of this research. We collected secondary data from a sample of 2479 solvers, representing the community of solvers registered in the 99design platform and still active until December 2019 (i.e., they have at least participated in one contest from December

2018 to December 2019, by submitting one or more solution proposals). Starting from this sample, we shaped the 99design crowdsourcing community network. Particularly, we built such a network considering the solvers' social interactions in the discussion blog of the 99designs platform. Then, we screened the profile of each solver embedded in the 99designs crowdsourcing community network to gather information about their success and past experiences within the platform, such as the number of contests won, their portfolio of designs, and their score rating.

Measures

The dependent variable of this study is the count variable *Contests won*, which measures the number of contests won by a solver. In 99designs' crowdsourcing platforms, the winner of the contest is chosen by the seeker who broadcasts the competition and asks to have solved a creative and innovation problem. The seeker selects the most creative and innovative solution as the winning one, according to the criteria defined in the problem statement (Piazza, Mazzola, and Perrone 2022). Prior crowdsourcing studies have already leveraged this variable for investigating the success of solvers in crowdsourcing contests (Zhu, Djurjagina, and Leker 2014).

Concerning the structural network embeddedness, we have used two independent variables, i.e. *Centrality* and *Structural Hole.* Considering *Centrality*, among the different network measures that have been previously used in literature, we use the eigenvector centrality because it considers for both direct and indirect ties (Moran 2005; Uzzi and Spiro 2005). According to such a measure, the most central solvers are those interacting with too many solvers, who in turn interact with many other solvers themselves. We choose eigenvector centrality since it is a good measure of information volume (Koka and Prescott 2002), that is what, in our theorizing, influences the development of innovative and creative ideas. Alongside this, in previous literature, it has been often related to innovation performance (Ahuja 2000; Mazzola, Perrone, and Kamuriwo 2015). Focusing on *Structural holes,* we measure it as one minus the firm's constraint score (in cases where constraint was non-zero) and zero for all other cases, because a score of zero in our network happens only when the solver is unconnected to others, so it has no access to structural holes. In previous literature, constraint is the most used measure for accounting of structural hole positions to assess the information diversity (Ahuja 2000; Shipilov and Li 2008). To compute both *Centrality* and *Structural Holes'* measures, we use UCINET VI (Borgatti, Everett, and Freeman 2002), a social network analysis software that computes network measurements.

Furthermore, several control variables have been considered in the analyses. We control for the influence that the period of *Membership* has on the success of a solver. We operationalized such a control variable as a continuous variable, measuring the natural logarithm of the number of days passed since the subscription of the solver. Furthermore, we included the variable *Repeated client*, a dummy variable that measures whether a solver has been awarded from the same seeker more than once. Such a variable allows us to control for the effect that the appreciation from seekers has on solvers success. Moreover, we control for the effect that the reputation system of the 99designs crowdsourcing platform has on the solvers' successes (Kokkodis and Ipeirotis 2016). Particularly, we leveraged two variables for controlling for the solvers' reputation within the 99sesigns crowdsourcing community. First, we used one of the most commonly agreed reputation measures in online platforms, i.e., the feedback rating (Hong and Pavlou 2017). Thus, we included in our analyses the variable *Stars,* a continuous variable measuring the review rating of the solvers (which range from 0 to 5 stars). Second, we leveraged the variable *Experience* by using three dummies (i.e., 'Entry-level, 'Mid-level', and 'Top-level') expressing the level of experience gathered by a solver in the 99designs platform. Finally, we controlled for the effect of the popularity of a solver among their peers by including the control variable *Hearts,* which is operationalized as a continuous variable measuring the natural logarithm of the number of likes solvers have received for their comments on the 99designs community blog.

ANALYSIS AND RESULTS

The descriptive statistics are provided in Table 1.

[Please insert Table 1 about here]

Table 2 shows the pairwise correlation values for all variables. The pairwise correlation matrix reveals no criticalities. Moreover, for all the models estimated, we calculated the variance inflation factor (VIF) values, a more advanced measure of multi-collinearity than simple correlations (Stevens 1996). The VIF values are below the critical level, suggesting that the variables can be included in the models simultaneously (Gujarati 2004). Once such precautions are taken, multi-collinearity poses no problems for this study.

[Please insert Table 2 about here]

Considering the nature of the dependent variable *Contest won*, to test our hypotheses, we performed a negative binomial regression analysis. Particularly, count data can follow a Poisson or a negative binomial regression distribution, however, overdispersion is a likely downside with the Poisson regression. As such, we tested the Poisson assumption alongside the negative binomial model via the goodness-of-fit (gof) test (Hausman, Hall, and Griliches 1984; Cameron and Trivedi 2013). Examined in contrast to the Poisson predictions for an equivalent model, the significant value for the chi-square in the gof test ($\chi 2 = 25976.41$, $p = 0.0000$) indicates that the Poisson distribution was not appropriate. Thus, the result suggests the use of the negative binomial specification for our analysis (Greene 2000).

The results of the estimations are reported in Table 3. Specifically, Model 1 operates as a baseline model, and it includes only the control variables. Model 2 introduces the independent variable *Centrality*, while Model 3 includes its quadratic effect to test Hypothesis 1. Similarly, Model 4 presents the independent variable *Structural Hole,* while Model 5 also comprises its quadratic effect to test Hypothesis 2. Finally, model 6 represents the complete model including both the independent variables and their quadratic effects to further test the two hypotheses advanced in this study.

[Please insert Table 3 about here]

Starting with the control variables, we focus on Model 1. The variable Membership is significant and has a positive coefficient, meaning that a longer membership period increases the number of contests won by a solver. Furthermore, *Repeated client* is significant and has a positive coefficient, suggesting that being awarded by the same seekers increases the number of contests won by a solver. Considering the dummy variables related to the solvers' *Experience*, 'Mid-level' and 'Top-level' are significant, and they present a positive coefficient. This result suggests that solvers who have greater experience in the 99designs platform ranking, win a higher number of contests compared to solvers in the 'Entry-level' (omitted since used as a baseline category). Similarly, the control variable *Stars* is significant and has a positive coefficient, meaning that the higher the rating of solvers, the greater their chances of being successful in crowdsourcing competitions. Finally, the control variable *Hearts* is significant, and it presents a positive coefficient, meaning that the number of contests won by a solver is affected by the likes they have received for their comments posted on the blog.

Moving on to the independent variables, in Model 3, *Centrality* is significant and has a positive impact on the number of contests won by a solver, while its squared term presents a significant and negative coefficient, thus supporting Hypothesis 1. Considering Model 5, the variable *Structural Hole* is significant and has a positive impact on the number of contests won by solvers. Moreover, the model also shows that the squared term of the explanatory variable is significant and has a negative coefficient, thus confirming Hypothesis 2. Lastly, Model 6 provides additional confirmation for the hypotheses of the study. Moreover, to further assess our results, we have provided graphical representations of the inverted U-shaped relationships in Figure 1 (Lind and Mehlum 2010; Haans, Pieters, and He 2015).

[Please insert Figure 1 about here]

Figure 1(a) provides further evidence that an inverted U-shaped relationship exists since the number of *Contest won* first increases with the *Centrality* of the solvers to reach a maximum, after which the number of *Contest won* decreases. The point at which the curve reaches its maximum, i.e., the 'turning point', should be located within the data range (Lind and Mehlum 2010; Haans, Pieters, and He 2015). Following the procedure suggested by Haans et al. (2015), we tested this assumption to further confirm the curvilinear relationship. Specifically, the turning point is positioned at 0.101 within Fieller's 95% confidence interval ([0.093 - 0.109]; p-value = 0.000). Furthermore, we performed the slop test to check the slope of the curve at its ends. Particularly, we assessed whether the slope is positive and significant at the lower-end of the curve and negative and significant at the upper-end. The results confirmed the interpretation of the inverted u-shaped relationship between *Centrality* and *Contest won*, suggesting that the slope of the curve is equal to 0.33 (p-value = 0.000) at the lower-end of the curve, and -0.37 (p-value = 0.000) at the upper-end.

Similarly, Figure 1(b) supports the inverted U-shaped relationship, highlighting that the number of *Contest won* first increases with the *Structural hole* position of the solvers, ultimately reaching a maximum, after which the number of *Contest won* decreases. Also, in this case, we performed the turning point test, which suggests it is located at 0.633 within the Fieller's 95% confidence interval ([-0.095 – 1.96]; p-value = 0.000). Finally, we also performed the slop test to provide further confirmation for the inverted u-shape relationship between *Blog activity* and *Contest won,* suggesting that the slope of the curve is equal to 0.62 (p-value = 0.000) at the lower-end, and -0.05 (p-value = 0.000) at the upper-end of the curve.

Robustness checks

To check for the robustness of the previous results, we carried out additional analyses. Specifically, we assessed the hypotheses by using an alternative dependent variable, i.e., *Finalist*, measuring for the number of times a solver reached the podium of the competition without winning (i.e., the solver ranked second or third). The results of this additional analysis, reported in Table 4, are consistent with those obtained using the main dependent variable *Contest won* (Table 3).

[Please insert Table 4 about here]

In addition, the solvers' positions within the crowdsourcing community network may change depending on their past successes. For instance, a solver might be more inclined toward interacting and chatting with more successful and leading peers, pushing themselves to increase their centrality position within the crowdsourcing community network (Becker et al. 2021). Such circumstances could represent potential reverse causalities and confounding issues in our main analyses. To address these issues, we assessed our hypotheses by using a lagged dependent variable, *Lagged contest won,* measuring for the number of contests won by a solver two years after the network construction. For measuring such a lagged dependent variable, we collected secondary data considering the performance measure of those solvers who had at least participated in one contest within December 2020 to December 2021, by submitting one or more solution proposals. Specifically, we found that only 1885 solvers out of 2479 from the initial sample were still active after two years. The results of this robustness analysis are reported in Table 5 and are consistent with those obtained using the main dependent variable *Contest won* (Table 3).

[Please insert Table 5 about here]

DISCUSSION AND CONCLUSIONS

By analyzing the network positions of 2479 solvers within the crowdsourcing community network of the 99designs platform and gathering information about their successes from their online profiles, we found two main results. First, we found support for the curvilinear (inverted U-shape) effect that occupying a central position within the crowdsourcing community network has on the solvers' likelihood of winning crowdsourcing contests. This result suggests that when reaching a position characterized by low- to intermediate-centrality, solvers are better able to develop more creative and innovative solutions and win crowdsourcing contests, by leveraging the high volume of information they can access from their peers in the network. However, as the centrality increases beyond a certain threshold, its benefits on solvers' successes are likely to diminish, because of the redundancy of information and the limited exploration possibilities, thereby impeding solvers from generating inventive solutions for winning crowdsourcing contests. Second, the findings support our hypothesis that occupying a structural hole position within the crowdsourcing community network has an inverted U-shaped effect on the success of solvers in crowdsourcing contests. Our results outline that recombining the diverse information that solvers can access from a structural hole position allows them to develop more creative and innovative solutions, and thus succeed in crowdsourcing contests. However, as solvers occupy a too structural hole position in the network, their possibilities of winning the contest are likely to diminish. Since, in such a circumstance, exploitative learning opportunities and the possibility of acquiring in-depth knowledge by establishing strong relationships are limited, thus solvers are restrained from generating creative and innovative solutions for winning crowdsourcing contests.

The results of this study offer several important theoretical contributions. First, this research contributes to prior literature which have investigated online communities as networks (Özaygen and Balagué 2018; Wang et al. 2020; Becker et al. 2021; Resch and Kock 2021). A majority of this early research was conducted not only in the context of open source software communities but also in the social network and user communities (Zhang and Wang 2012; Hwang, Singh, and Argote 2019;

Maruping, Daniel, and Cataldo 2019; Resch and Kock 2021; Safadi, Johnson, and Faraj 2021). Some scholars have highlighted how network positions indicate members' emergence as community leaders (Fleming and Waguespack 2007; Faraj, Kudaravalli, and Wasko 2015; Johnson, Safadi, and Faraj 2015; Kratzer et al. 2016; Lee et al. 2019; Becker et al. 2021), while others have examined the influence of the same on idea evaluation among community members (Özaygen and Balagué 2018). A few others have predicted members' participation and their willingness to contribute within the community by considering the network position (Zhang and Wang 2012; Maruping, Daniel, and Cataldo 2019; Wang et al. 2020). Finally, some other scholars have investigated how positioning in the community network impacts the members' abilities to develop valuable, creative and new ideas (Sosa 2011; Resch and Kock 2021; Safadi, Johnson, and Faraj 2021). However, these investigations have disregarded crowdsourcing community issues by adopting a structural network embeddedness perspective. Thus, showing how specific network positions affect solvers' successes in the crowdsourcing contests, we contribute to this stream of literature by highlighting the importance of also considering the network perspective, when investigating the online crowdsourcing communities.

Second, this study contributes to the literature investigating the solvers' success in crowdsourcing contests (Zhu, Djurjagina, and Leker 2014; Bockstedt, Druehl, and Mishra 2015; Bockstedt, Druehl, and Mishra 2016; Riedl and Seidel 2019). So far, these scholars have examined diverse behaviors that solvers should adopt and actions they should perform to increase their chances of being selected as winners (Zhu, Djurjagina, and Leker 2014; Bockstedt, Druehl, and Mishra 2015; Bockstedt, Druehl, and Mishra 2016; Riedl and Seidel 2019). For example, Zhu et al. (2014) found that the victory of a crowdsourcing contest depends on the solvers' ability to adopt alternative approaches to solve the seeker's problems. Moreover, Bockstedt et al. (2016) suggested how submitting solution proposals first and remaining active during the competition increase the solvers' likelihood of success. Finally, Riedl and Seidel (2019) suggested that to win a crowdsourcing contest, solvers should hone their solution proposals considering the suggestions they receive from the seeker throughout the competition. Even though this literature offers critical insights about the antecedents of the solvers' successes, all these previous scholars have taken up atomistic views, focusing exclusively on the actions and behaviors of individual solvers, disregarding how network relationships among solvers affect their success. The crowdsourcing platforms provide solvers with community functionalities (e.g., forum and discussion blogs) to chat, socialize and exchange knowledge and information among each other (Leimeister et al. 2009; Hutter et al. 2011). Thus, we are advancing previous crowdsourcing literature that have investigated solvers' successes, suggesting that alongside the already recognized deeds and behaviors, solvers can also increase their chances of being selected as winners by leveraging the knowledge and information flows they can access from within the crowdsourcing community network.

In addition, this study provides new insights into the literature that explores social interactions in online communities (Shen, Lee, and Cheung 2014; Faullant and Dolfus 2017; Hwang, Singh, and Argote 2019; Renard and Davis 2019; Jain and Deodhar 2021). This literature shows controversial evidence that has divided scholars between authors advocating the advantages of social interactions for members within the online community (e.g., Shen et al., 2014; Hwang et al., 2019; Renard and Davis, 2019) and those who also recognize the negative effects resulting from social interactions (e.g., Faullant and Dolfus 2017; Jain and Deodhar 2021). Particularly, the first cluster of authors suggest that interactions among members, by stimulating the competition among peers and allowing them to establish trustworthy and committed relationships, foster their contribution behaviors, enhance their creativity, and improve the quality of the generated ideas. On the other hand, the second cluster of authors stress that, below the surface, a higher level of competition, peculiar to the crowdsourcing communities, can stoke negative social interactions between members. For example, according to Faullant and Dolfus (2017), a fierce level of competition can incite solvers in trying to sabotage their peers by posting negative comments to bash their ideas, thereby discouraging them from advancing the quality of ideas generated, or even leading them to leave the contest. Our results support those authors who highlight the dual effect of social interactions among community members (e.g., Faullant and Dolfus 2017; Jain and Deodhar 2021), in opposition to those contributors who see only the good (e.g., Shen et al., 2014; Hwang et al., 2019; Renard and Davis, 2019). Indeed, by focusing on the structure of the network shaped by the solvers' social interactions, this paper shows that there are different effects (both positive and negative) associated with social interactions among solvers, within a crowdsourcing community. As such, this study contributes to previous literature exploring social interactions among community members, evidenced by the existence of a threshold in the relationship between different network positions and the success of community members. Specifically, this study adds to previous literature by suggesting that the effect of social interactions on community members' successes depend upon the number and diversity of peers with whom they exchange knowledge and information through posts and comments.

Managerial implications

Our study provides several implications for members participating in competitions within online communities, as well as for managers of online communities organizing these competitions. First, our results indicate the importance of the role played by the social interactions among members of a competitive online community. Members need to be conscious that exchanging information and sharing knowledge with their peers can affect their success. Specifically, members should be aware that establishing several relations with multiple peers within the community network allows them to gather a large volume of knowledge and information, to exploit for developing inventive solutions and winning the contest. However, an excessive number of connections or exchange of comments and feedback with peers who, in turn, have established several connections, increases the redundancy of information and limits the possibility to engage in exploratory processes. Consequently, this can reduce their likelihood of developing more inventive proposals to succeed in the competition. On the other hand, establishing connections with peers that are otherwise disconnected from each other, allows the leveraging of comments and feedbacks formulated by members from different perspectives. Recombining different information from community members can generate innovative and creative ideas, and thereby increase the chances of winning the competition. However, obtaining information from different sources may impede the members from generating innovative ideas, since such diversity reduces the reliability of the information, and thereby the ability to deepen the new knowledge. Thus, considering the above argumentations, community members could adopt a dynamic behavior in their positioning within an online community network, shifting over time through central and structural hole positions (and vice versa) to balance the explorative and exploitative advantages associated with the two network positions.

In addition, when planning the competition, managers of online communities must consider the role played by the social interactions among community members. In allowing community members to interact with each other through chats and comments, managers should be aware that this shapes the network structure of their online community. Thus, online communities' managers should appropriately design community functionalities – such as blogs or discussion boards – to allow members to exchange knowledge by establishing social interactions. Moreover, they should advise members about the number of interactions they have established with their peers, and the diversity of other members they are connected with, encouraging them to appropriately balance their chatting, posting, and commenting to take the best from these activities. By using network analysis, managers can differentiate structurally central actors to broker participants and advice community members about the positions they are assuming within the online community network.

Limitations and directions for further research

The results of this study should be considered in light of its limitations, which nevertheless provide opportunities for future research. First, this study focuses on a peculiar crowdsourcing platform, i.e., 99designs. Even though 99designs is an appropriate research setting for exploring the relationships between the structural embeddedness of a crowdsourcing community, and the solvers' successes, the results of this study cannot be extended to different kinds of crowdsourcing platforms (e.g., Innocentive and NineSigma). Indeed, not all crowdsourcing platforms allow solvers to interact with each other via forums, blogs and chats that is sharing knowledge and information through posts and comments. Also, different crowdsourcing platforms may provide solvers with diverse tools to engage in social interactions, beyond the discussion blog. For instance, other crowdsourcing platforms may provide solvers with a private chatting system. As such, future studies might replicate our analysis by considering different crowdsourcing platforms that provide diverse community functionalities, to investigate how social interactions among solvers affect their likelihood of winning these contests.

Second, to build the 99designs crowdsourcing community network, we only considered whether two solvers have interacted with each other in the discussion blog of the platform. Although we gained clarity about the relationship between the solvers' positions within the network, and their success, we could not address interesting questions related to the quality of knowledge and information exchanged by solvers engaged in posting and commenting. Applying diverse research methods, such as content analysis, future studies can provide a better understanding of the variations of the impact that sharing specific knowledge and information has on the success of solvers participating in crowdsourcing competitions.

Finally, another limitation is that our analyses are based on secondary data. Since secondary data already exists, new constructs of interest cannot be added to the analysis. Furthermore, secondary data analysis cannot provide a confirmatory empirical analysis based on direct experiences, to demonstrate whether the assumptions about the data interpretations are appropriate. Thus, future research can analyse how exchanging knowledge and information among peers in the crowdsourcing community can improve the solvers' likelihood of succeeding in a contest, by conducting multiple case studies or a survey. For example, by interviewing the solvers, future studies may enrich the understanding of the role played by social interaction among peers, especially by asking them how receiving comments and feedbacks push them to improving their solution proposals and winning the competition. Moreover, we assumed in our analysis that to solve creative problems, solvers access knowledge solely from the crowdsourcing community. However, this is not the unique 'great good places' from where solvers can access knowledge. For example, they can be simultaneously members of several online communities and gather knowledge and information from multiple sources. Thus, in interviewing solvers, future studies can overcome this limitation and consider the interactions of multiple networks.

TABLE AND FIGURES

Variable	Min	Max	Mean	Sd.dev.
(1) Contests won	0	458	24.53	40.6
(2) Finalist	0	1355	52.66	0.61
(3) Membership	3.33	8.51	7.05	0.44
(4) Repeated client	0	7.19	1.21	0.50
(5) Entry Level	0	1	0.27	0.46
(6) Mid-Level	0	1	0.43	1.34
(7) Top Level	0	1	0.30	0.29
(8) Hearts	0.69	10.05	2.**66**	0.35
(9) Stars	0	5	0.19	0.54
(10) Centrality	0	0.22	0.01	0.03
(11) Structural hole	0	1	0.48	0.33

Table 1. Descriptive statistics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Contests won	1										
(2) Finalist	0.318*	1									
(3) Membership	0.305*	0.276*	1								
(4) Repeated client	0.714*	0.585	0.398*	1							
(5) Entry Level	-0.296*	-0.257*	-0.266*	-0.466*	1						
(6) Mid Level	-0.113*	-0.055*	-0.059*	-0.141*	-0.530*	1					
(7) Top Level	0.411*	0.310*	0.323*	0.606*	-0.402*	-0.564*	1				
(8) Hearts	0.197*	0.164*	0.062*	0.315*	-0.284*	-0.043*	0.323*	1			
(9) Stars	0.005	0.024	0.051*	0.134*	-0.242*	0.165*	0.056*	0.129*	1		
(10) Centrality	0.376*	0.209*	0.080*	0.306*	-0.174*	-0.0780*	0.254*	0.538*	0.014	1	
(11) Structural hole	0.135*	0.046*	0.078*	0.191*	-0.170*	-0.013	0.179*	0.433*	0.070*	0.444*	1

* $p < 0.05$

Table 2. Correlation matrix

	Contest won					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Membership	0.621***	0.619***	0.623***	0.621***	0.620***	0.624***
	(0.0490)	(0.0591)	(0.0596)	(0.0592)	(0.0587)	(0.0591)
Repeated client	0.928***	0.931***	0.916***	0.928***	0.928***	0.912***
	(0.0198)	(0.0244)	(0.0243)	(0.0244)	(0.0242)	(0.0243)
Mid Level	0.623***	0.623***	0.614***	0.620***	0.618***	0.614***
	(0.0491)	(0.0681)	(0.0681)	(0.0683)	(0.0675)	(0.0673)
Top_Level	0.467***	0.468***	0.464***	0.464***	0.465***	0.469***
	(0.0602)	(0.0812)	(0.0811)	(0.0812)	(0.0797)	(0.0796)
Hearts	0.0212*	0.0268*	0.00816	0.0185	0.0266*	0.0145
	(0.00942)	(0.0121)	(0.0129)	(0.0117)	(0.0118)	(0.0129)
Stars	0.880***	0.872***	0.872***	0.882***	0.866***	0.858***
	(0.0724)	(0.0861)	(0.0857)	(0.0862)	(0.0862)	(0.0854)
Centrality		0.296	0.200***			0.244***
		(0.0265)	(0.0507)			(0.0555)
Centrality^2			-0.0482***			-0.0526***
			(0.00988)			(0.0109)
Structural hole				0.0448	0.685***	0.605**
				(0.0641)	(0.208)	(0.207)
Structural hole^2					-0.749***	-0.791***
					(0.219)	(0.219)
Constant	-3.760***	-3.763***	-3.671***	-3.771***	-3.837***	-3.712***
	(0.347)	(0.408)	(0.413)	(0.410)	(0.409)	(0.413)
N	2479	2479	2479	2479	2479	2479
Log-likelihood	-8494.57	-8493.75	-8476.78	-8494.30	-8486.98	-8468.36
Chi-square test	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood ratio test		1.65	33.93***	0.54	14.64***	52.42***

Standard errors in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3. Negative binomial regression results – Contests won

	Finalist					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Membership	0.722***	0.722***	0.714***	0.722***	0.722***	0.714***
	(0.0500)	(0.0674)	(0.0682)	(0.0674)	(0.0679)	(0.0686)
Repeated client	0.837***	0.839***	0.821***	0.838***	0.837***	0.817***
	(0.0224)	(0.0266)	(0.0262)	(0.0264)	(0.0264)	(0.0266)
Mid Level	0.615***	0.615***	0.610***	0.612***	0.613***	0.615***
	(0.0526)	(0.0733)	(0.0728)	(0.0730)	(0.0729)	(0.0720)
Top_Level	0.351***	0.351***	0.354***	0.349***	0.349***	0.361***
	(0.0663)	(0.0860)	(0.0851)	(0.0858)	(0.0855)	(0.0844)
Hearts	0.0415***	0.0439***	0.0249+	0.0395**	0.0425**	0.0287*
	(0.0110)	(0.0133)	(0.0132)	(0.0135)	(0.0137)	(0.0133)
Stars	0.902***	0.899***	0.900***	0.904***	0.897***	0.893***
	(0.0819)	(0.0983)	(0.0972)	(0.0985)	(0.0990)	(0.0971)
Centrality		0.127	0.224***			0.252***
		(0.0346)	(0.0635)			(0.0705)
Centrality^2			-0.0482***			-0.0514***
			(0.0111)			(0.0122)
Structural hole				0.323	0.323*	0.222*
				(0.769)	(0.245)	(0.243)
Structural hole^2					-0.338**	-0.346*
					(0.260)	(0.262)
Constant	-3.492***	-3.494***	-3.323***	-3.499***	-3.532***	-3.323***
	(0.353)	(0.467)	(0.473)	(0.469)	(0.475)	(0.479)
N	2479	2479	2479	2479	2479	2479
Log-likelihood	-10657.83	-10657.71	-10643.74	-10657.72	-10656.49	-10641.91
Chi-square test	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood ratio test		0.24	27.95***	0.23	10.22***	31.84***

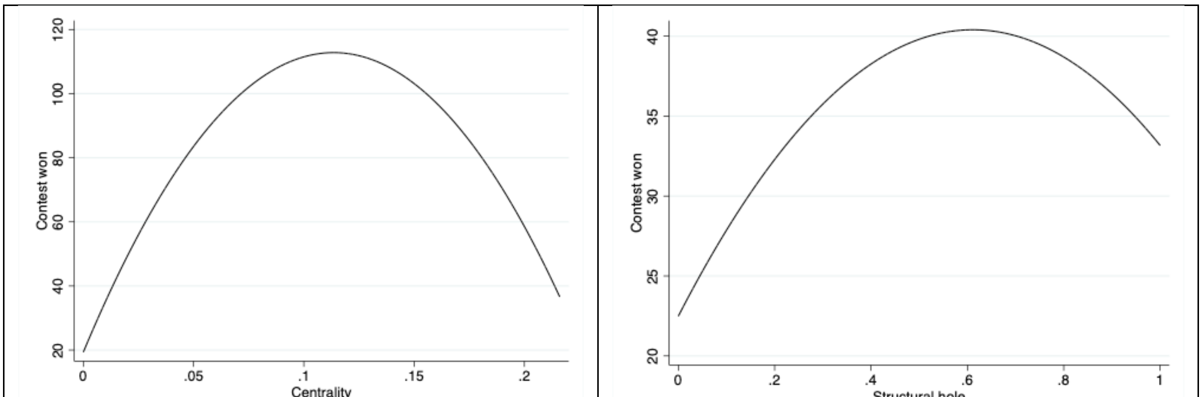
Standard errors in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Negative binomial regression results – Finalist

	Lagged Contest won					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Membership	0.0924^{+}	0.0942^{+}	0.0920^{+}	0.0916^{+}	0.0854	0.0839
	(0.0549)	(0.0549)	(0.0544)	(0.0550)	(0.0549)	(0.0543)
Repeated client	0.841***	0.838***	0.823***	0.840***	0.840***	0.815***
	(0.0226)	(0.0229)	(0.0228)	(0.0226)	(0.0226)	(0.0228)
Mid Level	0.375***	0.374***	0.370***	0.377***	0.373***	0.372***
	(0.0618)	(0.0618)	(0.0612)	(0.0619)	(0.0618)	(0.0611)
Top_Level	0.262***	0.262***	0.267***	0.264***	0.264***	0.279***
	(0.0728)	(0.0728)	(0.0720)	(0.0729)	(0.0728)	(0.0719)
Hearts	0.0246*	0.0209^{+}	0.000940	0.0281*	0.0360**	0.0130
	(0.0108)	(0.0121)	(0.0125)	(0.0118)	(0.0121)	(0.0128)
Stars	0.596***	0.603***	0.606***	0.595***	0.575***	0.587***
	(0.0822)	(0.0828)	(0.0824)	(0.0821)	(0.0818)	(0.0816)
Centrality		0.0188	0.254***			0.335***
		(0.0272)	(0.0520)			(0.0570)
Centrality^2			-0.0498***			-0.0592***
			(0.00892)			(0.00932)
Structural hole				-0.0528	0.510*	0.442*
				(0.0719)	(0.212)	(0.211)
Structural hole^2					-0.659**	-0.772***
					(0.234)	(0.234)
Constant	-0.277***	-0.278***	-0.295***	-0.278***	-0.282***	-0.307***
	(0.0365)	(0.0365)	(0.0366)	(0.0365)	(0.0365)	(0.0367)
N	1885	1885	1885	1885	1885	1885
Log-likelihood	-7680.3947	-7680.1524	-7665.8195	-7680.1248	-7676.1891	-7656.69
Chi-square test	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood ratio test		0.48	28.67***	0.54	7.87**	39.00***

Standard errors in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Negative binomial regression results – Lagged Contest won



(a) (b)

Figure 1. Inverted U-shape relationships

REFERENCES

Ahuja, G. 2000. Collaboration Networks , Structural Holes , and Innovation : A Longitudinal Study. *Administrative Science Quarterly* 45 (3): 425–55.

Becker, L., K. Coussement, M. Büttgen, and E. Weber. 2021. Leadership in innovation communities: The impact of transformational leadership language on member participation. *Journal of Product Innovation Management*: jpim.12588.

Björk, J., and M. Magnusson. 2009. Where do good innovation ideas come from? Exploring the influence of network connectivity on innovation idea quality. *Journal of Product Innovation Management* 26 (6): 662–70.

Bockstedt, J., C. Druehl, and A. Mishra. 2015. Problem-solving effort and success in innovation contests: The role of national wealth and national culture. *Journal of Operations Management* 36 (December 2014). Elsevier B.V.: 187–200.

Bockstedt, J., C. Druehl, and A. Mishra. 2016. Heterogeneous Submission Behavior and its Implications for Success in Innovation Contests with Public Submissions. *Production and Operations Management* 25 (7): 1157–76.

Bogers, M., N. J. Foss, and J. Lyngsie. 2018. The "human side" of open innovation: The role of employee diversity in firm-level openness. *Research Policy* 47 (1). Elsevier: 218–31.

Borgatti, S. P., M. G. Everett, and L. C. Freeman. 2002. *UCINET 6 for Windows: Software for social network analysis (Version 6.102). Harvard, ma: analytic technologies*. Harvard, Technologies, MA: Analytic.

Burt, R. S. 1992. *Structural Holes: The Social Structure of Competition*. Cambridge: Harvard University Press.

Burt, R. S. 2001. The Social Capital of Structural Holes. In . New York: Russell Sage Foundation.

Cameron, A. C., and P. K. Trivedi. 2013. *Regression analysis of count data*. Cambridge university press.

Chan, K. W., S. Y. Li, and J. J. Zhu. 2015. Fostering Customer Ideation in Crowdsourcing Community: The Role of Peer-to-peer and Peer-to-firm Interactions. *Journal of Interactive Marketing* 31. Elsevier B.V.: 42–62.

Cohen, W. M., and D. A. Levinthal. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly* 35: 128–52.

Dahlander, L., and L. Frederiksen. 2012. The Core and Cosmopolitans: A Relational View of Innovation in User Communities. *Organization Science* 23 (4): 988–1007.

Faraj, S., and S. L. Johnson. 2011a. Network Exchange Patterns in Online Communities. *Organization Science* 22 (6): 1464–80.

Faraj, S., and S. L. Johnson. 2011b. Network Exchange Patterns in Online Communities. *Organization Science* 22 (6): 1464–80.

Faraj, S., S. Kudaravalli, and M. Wasko. 2015. Leading collaboration in online communities. *MIS Quarterly: Management Information Systems* 39 (2): 393–412.

Faraj, S., G. von Krogh, E. Monteiro, and K. R. Lakhani. 2016. Special Section Introduction—Online Community as Space for Knowledge Flows. *Information Systems Research* 27 (4): 668–84.

Faullant, R., and G. Dolfus. 2017. Everything community? Destructive processes in communities of crowdsourcing competitions. *Business Process Management Journal* 23 (6): 1108–28.

Fleming, L., and D. M. Waguespack. 2007. Brokerage, Boundary Spanning, and Leadership in Open Innovation Communities. *Organization Science* 18 (2): 165–80.

Freeman, C. 1991. Networks of innovators: A synthesis of research issues. *Research Policy* 20 (5): 499–514.

Galaskiewicz, J. 1979. The structure of community organizational networks. *Social forces* 57 (4): 1346–64.

Ganley, D., and C. Lampe. 2009. The ties that bind: Social network principles in online communities. *Decision Support Systems* 47 (3): 266–74.

Garcia Martinez, M. 2015. Solver engagement in knowledge sharing in crowdsourcing communities: Exploring the link to creativity. *Research Policy* 44 (8): 1419–30.

Garcia Martinez, M. 2017. Inspiring crowdsourcing communities to create novel solutions: Competition design and the mediating role of trust. *Technological Forecasting and Social Change* 117. Elsevier Inc.: 296–304.

Gilsing, V., B. Nooteboom, W. Vanhaverbeke, G. Duysters, and A. Van Den Oord. 2008. Network embeddedness and the exploration of novel technologies : Technological distance , betweenness centrality and density. *Research Policy* 37: 1717–31.

Granovetter, M. S. 1992. Problems of explanation in economic sociology. In *Networks and Organizations: Structure, Form and Action.*, 25–56. Boston, Massachusetts: Harvard Business School Press.

Greene, W. H. 2000. *Econometric analysis*. Upper Saddle River, NJ: Prentice Hall.

Gujarati, D. N. 2004. *Basic Econometrics 4ed*. *The McGraw-Hill Companies*.

Gulati, R., N. Nohria, and A. Zaheer. 2000. Strategic networks. *Strategic Management Journal* 21 (3): 203–15.

Haans, R. F. J., C. Pieters, and Zi. L. He. 2015. Thinking about U: Theorizing and Testing U- and Inverted U-shaped relationships in strategy research. *Strategic Management Journal* 37: 1177–95.

Hausman, J., B. H. Hall, and Z. Griliches. 1984. Econometric Models for Count Data with an Application to the Patents-R & D Relationship. *Econometrica* 52 (4): 909–38.

Hong, Y., and P. A. Pavlou. 2017. On buyer selection of service providers in online outsourcing platforms for IT services. *Information Systems Research* 28 (3): 547–62.

Hutter, K., J. Hautz, J. Füller, J. Mueller, and K. Matzler. 2011. Communitition: The tension between competition and collaboration in community-based design contests. *Creativity and Innovation Management* 20 (1): 3–211.

Hwang, E. H., P. V. Singh, and L. Argote. 2019. Jack of all, master of some: Information network and innovation in crowdsourcing communities. *Information Systems Research* 30 (2): 389–410.

Jain, S., and S. J. Deodhar. 2021. Social mechanisms in crowdsourcing contests: a literature review. *Behaviour and Information Technology*: 1–35.

Johnson, S. L., H. Safadi, and S. Faraj. 2015. The emergence of online community leadership. *Information Systems Research* 26 (1): 165–87.

Katila, R., and G. Ahuja. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal* 45 (6): 1183–94.

Koka, B. R., and J. E. Prescott. 2002. Strategic alliances as social capital: A multidimensional view. *Strategic Management Journal* 23: 795–816.

Koka, B. R., and J. E. Prescott. 2008. Designing alliance networks: the influence of network position , environmental change , and strategy on firm performance. *Strategic Management Journal* 29(6): 639–661.

Kokkodis, M., and P. G. Ipeirotis. 2016. Reputation transferability in online labor markets. *Management Science* 62 (6): 1687–706.

Kratzer, J., C. Lettl, N. Franke, and P. A. Gloor. 2016. The Social Network Position of Lead Users. *Journal of Product Innovation Management* 33 (2): 201–16.

Lee, J. Y.-H., C.-S. Yang, C. Hsu, and J.-H. Wang. 2019. A longitudinal study of leader influence in sustaining an online community. *Information & Management* 56 (2): 306–16.

Leimeister, J., M. Huber, U. Bretschneider, and H. Krcmar. 2009. Leveraging crowdsourcing: Activation-supporting components for IT-based ideas competition. *Journal of Management Information Systems* 26 (1): 197–224.

Levinthal, D. A., and J. G. March. 1993. The Myopia of Learning. *Strategic Management Journal* 14: 95–112.

Lind, J. T., and H. Mehlum. 2010. With or without u? the appropriate test for a U-shaped relationship. *Oxford Bulletin of Economics and Statistics* 72 (1): 109–18.

March, J. G. 1991. Exploration and Exploitation in Organizational Learning. *Organization Science* 2 (1): 71–87.

Maruping, L. M., S. L. Daniel, and M. Cataldo. 2019. Developer centrality and the impact of value congruence and incongruence on commitment and code contribution activity in open source software communities. *MIS Quarterly* 43 (3): 951–76.

Mazzola, E., G. Perrone, and D. S. Kamuriwo. 2015. Int . J . Production Economics Network embeddedness and new product development in the biopharmaceutical industry : The moderating role of open innovation fl ow. *Intern. Journal of Production Economics* 160. Elsevier: 106–19.

Mazzola, E., G. Perrone, and R. Handfield. 2018. Change Is Good, But Not Too Much: Dynamic Positioning in the Interfirm Network and New Product Development. *Journal of Product Innovation Management* 00 (00).

Mazzola, E., N. Acur, M. Piazza, and G. Perrone. 2018. "To Own or Not to Own?" A Study on the Determinants and Consequences of Alternative Intellectual Property Rights Arrangements in Crowdsourcing for Innovation Contests. *Journal of Product Innovation Management* 35 (6): 908–29.

Mazzola, E., M. Piazza, N. Acur, and G. Perrone. 2020. Treating the crowd fairly: Increasing the solvers' self-selection in idea innovation contests. *Industrial Marketing Management* 91 (July). Elsevier: 16–29.

Moran, P. 2005. Structural vs. relational embeddedness: Social capital and managerial performance. *Strategic Management Journal* 26 (12): 1129–51.

Nahapiet, J., and S. Ghoshal. 1998. Social Capital , Intellectual Capital , and the Organizational Advantage. *The Academy of Management Review* 23 (2): 242–66.

Natalicchio, A., A. Messeni Petruzzelli, and A. C. Garavelli. 2014. A literature review on markets for ideas: Emerging characteristics and unanswered questions. *Technovation* 34 (2). Elsevier: 65–76.

Natalicchio, A., A. Messeni Petruzzelli, and A. C. Garavelli. 2017. Innovation problems and search for solutions in crowdsourcing platforms – A simulation approach. *Technovation* 64–65 (November 2015). Elsevier Ltd: 28–42.

Ogink, T., and J. Q. Dong. 2019. Stimulating innovation by user feedback on social media: The case of an online user innovation community. *Technological Forecasting and Social Change* 144 (March 2016). Elsevier: 295–302.

Özaygen, A., and C. Balagué. 2018. Idea evaluation in innovation contest platforms: A network perspective. *Decision Support Systems* 112: 15–22.

Perry-Smith, J. E., and P. V. Manucci. 2017. From Creativity to Innovation: the Social Network Drivers of the Four Phases od the Idea Journey. *Academy of Management Review* 42 (1): 43–59.

Piazza, M., E. Mazzola, and G. Perrone. 2022. How can I signal my quality to emerge from the crowd? A study in the crowdsourcing context. *Technological Forecasting and Social Change* 176: 121473.

Renard, D., and J. G. Davis. 2019. Social interdependence on crowdsourcing platforms. *Journal of Business Research* 103 (July). Elsevier: 186–94.

Resch, C., and A. Kock. 2021. The influence of information depth and information breadth on brokers' idea newness in online maker communities. *Research Policy* 50 (8): 104142.

Riedl, C., and V. P. Seidel. 2019. Learning from mixed signals in online innovation communities. *Organization Science* 29 (6): 1010–32.

Ruiz, É., S. Brion, and G. Parmentier. 2020. Absorbing knowledge in the digital age: the key role of integration mechanisms in the context of crowdsourcing for innovation. *R and D Management* 50 (1): 63–74.

Safadi, H., S. L. Johnson, and S. Faraj. 2021. Who Contributes Knowledge? Core-Periphery Tension in Online Innovation Communities. *Organization Science* 32 (3): 752–75.

Shen, X. L., M. K. O. Lee, and C. M. K. Cheung. 2014. Exploring online social behavior in crowdsourcing communities: A relationship management perspective. *Computers in Human Behavior* 40. Elsevier Ltd: 144–51.

Shipilov, A. V., and S. X. Li. 2008. Can you have your Cake and Eat it too? Structural Holes' Influence on Status Accumulation and Market Performance in Collaborative Networks. *Administrative Science Quarterly* 58 (1): 73–108.

Sosa, M. E. 2011. Where Do Creative Interactions Come From? The Role of Tie Content and Social Networks. *Organization Science* 22 (1): 1–21.

Stevens, J. 1996. *Applied multivariate statistics for the social sciences (3rd Edition). Mahwah, NJ: Lawrence Erlbaum*.

Sun, Y., and S. Grimes. 2017. Technological Forecasting & Social Change The actors and relations in evolving networks : The determinants of inter- regional technology transaction in China. *Technological Forecasting & Social Change* 125 (October 2016). Elsevier: 125–36.

Uzzi, B., and J. Spiro. 2005. Collaboration and creativity: The small world problem. *American Journal of Sociology* 111 (2): 447–504.

Wang, X., T. T. Ow, L. Liu, Y. Feng, and Y. Liang. 2020. Effects of peers and network position on user participation in a firm-hosted software community: the moderating role of network centrality. *European Journal of Information Systems* 29 (5): 521–44.

Zaheer, A., and G. G. Bell. 2005. Benefiting from network position: Firm capabilities, structural holes, and performance. *Strategic Management Journal* 26 (9): 809–25.

Zhang, X., and C. Wang. 2012. Network Positions and Contributions to Online Public Goods: The Case of Chinese Wikipedia. *Journal of Management Information Systems* 29 (2): 11–40.

Zhu, H., K. Djurjagina, and J. Leker. 2014. Innovative behaviour types and their influence on individual crowdsourcing performances. *International Journal of Innovation Management* 18 (6).

Zhu, H., A. Kock, M. Wentker, and J. Leker. 2019. How Does Online Interaction Affect Idea Quality? The Effect of Feedback in Firm-Internal Idea Competitions. *Journal of Product Innovation Management* 36 (1): 24–40.