Treating the Crowd Fairly: Increasing the solvers' self-selection in idea crowdsourcing contests

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Abstract

The success of idea crowdsourcing contests depends on the wideness of the number of solvers that voluntarily self-select to solve the problem broadcast by the seeker and previous research has started to highlight the role of fairness in the self-selection process of solvers. This study aims at deepening the understanding concerning how fairness can influence the solvers' self-selection. By applying a netnographic research design, we identify possible unexplored facets of fairness in the crowdsourcing context, i.e., prize award, award guaranteed, and non-blind contest. Theoretically, we drew from the organizational justice and fairness literature to develop hypotheses about how the three fairness elements affect solvers' participation in idea crowdsourcing contests. Then, to empirically test the hypotheses, we performed an econometric analysis building on a distinctive dataset of 1067 contests, broadcast on the 99designs crowdsourcing platform. We found that the three fairness factors which emerged from the netnography have a positive impact on the self-selection of solvers. The results of this study offer important contributions to previous literature and provide several implications for organizations and contest organizers in the idea crowdsourcing context.

INTRODUCTION

To source new ideas and innovation from beyond their boundaries, organizations (seekers) are increasingly turning to idea crowdsourcing contests (Andersen et al., 2013; Steils and Hanine, 2019). Idea crowdsourcing contests are organized as competitions among solutions' providers (solvers) aiming to fulfill seekers' creativity and innovation needs such as the design of business logos and the development of new products (Natalicchio et al., 2017; Schemmann et al., 2016).

In this context, one of the major challenges for seekers is to foster the participation of solvers, which is on a voluntary basis (Pollok et al., 2019). Seekers announce their needs through problem statements broadcast on crowdsourcing platforms, solvers screen such problem statements, assess the information disclosed by seekers and, then, deliberately decide whether to self-select by submitting solutions (Afuah and Tucci, 2012; Mazzola et al., 2018; Pollok et al., 2019; Sieg et al., 2010). The challenge for seekers is to design contests that significantly impact the motivations and self-selection process of a large pool of solvers. Attracting a wide number of solvers allows seekers to receive more diverse and creative solutions, thereby improving the possibility of receiving, at a minimum, one suitable solution (Jeppesen and Lakhani, 2010; Terwiesch and Xu, 2008). Recognizing the participation of solvers as crucial to increase the success of contests; previous crowdsourcing scholars have deeply investigated how seekers can stimulate the solvers' self-selection from different perspectives. These scholars have investigated several factors that seekers can leverage to boost the self-selection process including intrinsic and extrinsic motivations (e.g., Acar, 2019; Boons et al., 2015; Garcia Martinez, 2017; Liang et al., 2018; Ye and Kankanhalli, 2017), the design of the contest (e.g., Erat and Krishnan, 2012; Jian et al., 2019; Mazzola et al., 2018; Pollok et al., 2019; Wooten and Ulrich, 2017; Zheng et al., 2011) and the competition intensity during the contest (e.g., Li and Hu, 2017; Shao et al., 2012). Moreover, another critical factor that crowdsourcing literature recognizes as a catalyst for solvers' participation is that of solvers' fairness perceptions (i.e., Franke et al., 2013; Zou et al., 2015; Faullant et al. 2017). These scholars focus on the effect that fairness aspects such as the allocation of resources and the procedure regulating the competition have on solvers' decisions to participate in a crowdsourcing contest. For example, Franke et al., (2013) use what they term "anticipatory action" as an approach to examining the predictive role of fairness perceptions ex ante to participation. They employ a simulation scenario that describes how the crowdsourcing tournament's terms and conditions affect the solvers' intention to participate. As Cropanzano and Folger (1989) and Greenberg (1987) indicate, whether these simulation interactions could be generalized to real organizational settings is questionable. Although Faullant et al. (2017) analyze one real-life crowdsourcing contest designed by a manufacturer company based on survey to analyze the fairness effect on solvers' perceptions of customer relation-related consequences, their empirical study could not be generalized as based on a survey as well as only one particular contest. Some organizations use intermediary firms in innovation activities, which act as knowledge brokers for idea generation. Such firms leverage a broad community of people in the creation and development of innovative ideas, obtaining and sharing new knowledge (Howells 2006).

The notion of fairness in working environments has become highly visible and has received considerable research attention (e.g., Colquitt et al., 2005; Cropanzano et al., 2015). Previous fairness literature stresses the complexity of the fairness concept highlighting its multifaceted nature that encompasses several dimensions among which are, for instance, distributive fairness, i.e., fairness in the allocation of resources, and procedural fairness, i.e., fairness about the procedures regulating the allocation of resources (Brockner et al., 2015; Cropanzano et al., 2015; Rupp et al., 2017). Moreover, fairness literature suggests that the concept of fairness can assume different meanings depending on what kinds of resources have to be allocated and based on the specific context analyzed (Brady and Dunn, 1995; Colquitt, 2001). For example, leveraging merit-based criteria, such as the educational background of people, is considered as fair for allocating job positions to job applicants but it cannot be related to the concept of fairness when considering the distribution of economical aids to the population. Thus, since fairness is a multidimensional, complex and context-dependent construct that defies simple definitions (Colquitt, 2001), we wonder whether, besides the few factors investigated by prior crowdsourcing scholars (i.e., Franke et al., 2013; Zou et al., 2015), others can be related to the concept of fairness in the solvers' self-selection process. Particularly, we intend to further explore factors that induce solvers to perceive they will be treated fairly by seekers and lead them to participate in a crowdsourcing contest. To identify possible further facets of fairness in a real crowdsourcing context, we perform a netnographic analysis (Kozinets, 2002) by leveraging qualitative data gathered from the 99designs crowdsourcing platform. The netnography allows us to gather evidence of further elements that shape solvers' perceptions of fairness: prize award, award guaranteed, and non-blind contest. Thus, the main aim of this paper is to investigate how these new elements, which frame the concept of fairness, impact the solvers' self-selection in crowdsourcing contests.

Shedding new light on the discussion around the fairness concept in the crowdsourcing context could be beneficial for harnessing the potential of crowdsourcing contests. A more comprehensive and rich definition of fairness deepens seekers' understanding of the factors that lead solvers to perceive a crowdsourcing contest as fair (Colquitt, 2001; Brockner et al., 2015). These new factors give seekers more information to design fair contests in accordance with solvers' expectations and desires. Thus, leveraging novel fairness elements empowers seekers to face the challenge of fostering the solvers' participation in their crowdsourcing contests.

Theoretically, we drew from the organizational justice and fairness literature (e.g., Cohen-Charash and Spector, 2001; Gilliland, 1993; Leventhal, 1980; Franke et al., 2013; Zou et al., 2015) to develop hypotheses concerning how the three fairness elements (i.e., prize award, award guaranteed, and non-blind) affect solvers' participation. Then, to empirically test the hypotheses, we performed an econometric analysis building on a distinctive dataset of 1067 contests, broadcast on the 99designs crowdsourcing platform.

The present research offers several contributions to previous literature investigating the role of fairness in the crowdsourcing context (i.e., Faullant and Dolfus, 2017; Fieseler et al., 2019; Franke et al., 2013; Zou et al., 2015). Considering the participation of the challenge as the number of solvers that have actually self-selected in the challenge by submitting a solution, we contribute to previous crowdsourcing literature (e.g. Franke et al., 2013) by investigating the effects of fairness *ex post* to participation rather than *ex ante*. In our work, we examine the influence fairness plays in attracting solvers in an actual scenario by using secondary data. We believe this approach spreads the external validity of our work since we collect data on real behaviors rather than intentions or only one contest which was designed by a seeker. We also use a real idea generation platform which hosts and enables idea generation projects and is being employed for different design activities: it acts as a community of practice, a co-laboratory for articulating key research issues around innovation, sharing experiences and developing and implementing experiments to develop new idea generation tools, including new approaches to motivate participants. In addition, this study also contributes to the extant crowdsourcing literature examining how seekers can influence the participation of solvers by leveraging the design of contests and the information included in the problem statements (e.g., Boudreau et al., 2011; Erat and Krishnan, 2012; Mazzola et al., 2018; Pollok et al., 2019). Moreover, this paper offers contributions to the discourse about value capture in the crowdsourcing context (e.g., Afuah and Tucci, 2013; Chesbrough et al., 2018). Suggesting that fair contests can simultaneously satisfy solvers' expectations of ethics and respect, and provide seekers access to a wide number of solution proposals, this paper highlights the role of fairness as a value-capturing mechanism for both seekers and solvers. Finally, this paper provides critical implications for seeker organizations that broadcast creativity and innovation needs through idea crowdsourcing contests by suggesting to them how to design contests perceived by solvers as fair.

NETNOGRAPHIC APPROACH

To explore the concept of fairness and identify further factors related to the solvers' fairness perceptions, we conducted a netnography (Kozinets, 2002) in the 99designs community. The netnography is an interpretative method, adapted from ethnography, for studying online communities, such as crowdsourcing communities (Kozinets, 2010). Following the approach of previous scholars (e.g., Yousaf and Xiucheng, 2018), we particularly performed an observational netnography, meaning that the authors do not reveal their presence to the community and do not intervene in the interactions among solvers. The unobtrusive nature of this approach allowed us to interpret the empirical context, analyzing non-elicited and non-biased data retrieved by observing solvers socializing and interacting among them (Kozinets, 2010).

99designs is a leading crowdsourcing platform in the market of online graphic design such as logos, business cards and web design (99designs, 2019; Bauer et al., 2016) and it appeared as an appropriate empirical setting for conducting the netnography. Indeed, 99designs has a blog where designers (i.e. solvers) actively debate on their experience and expectations, ask for feedback about their proposals, share their feelings, and ask for information about the rules of the contests. Such content allows the collection of qualitative data to conduct the netnography and identify factors related to the solvers' fairness perceptions.

Netnography data collection

We applied the netnography procedure suggested by Kozinets (2002). In the first step, called the entrée, two of the authors registered themselves as members of the 99designs community, observed the interactions among solvers and read their discussion posts. This step allows authors to learn about the language, culture and life of the community.

Then, the solvers' discussions of the 99designs blog were collected. The 99designs blog contains more than 8700 discussions, with billions of posts. To deal with such a large amount of information and find relevant discussions, the two authors conducted a systematic search. Since we aim to find fairness factors, the two authors paid attention to those discussions in which solvers talk about fairness-related issues. Specifically, to find relevant discussions, a heuristic search was performed based on keywords. To develop a list of keywords, firstly, each author individually drafted her/his initial list and then, together, analyzed the lists to remove or add some other keywords (Paulus 2000). The final list of keywords is '*fair*', 'justice', 'equit*', '*honest*', 'right*', 'correct*', 'wrong*', 'integrity', 'ethic*', and 'transparen*' [1]. Then, the authors searched and select those discussions that include one or more keywords. Finally, following some previous studies (e.g., Parsloe, 2015), the authors selected only those discussions containing at least 10 posts to capture the most representative fairness-related issues.

The selection of relevant discussions resulted in an initial database of 167 discussions subsequently screened to remove any false positive cases that may lead to biased results, i.e., discussions containing the keywords but unrelated to the solvers' fairness perceptions. The final database consisted of 54 relevant discussions. Table 1 reports the number of relevant discussions for each keyword.

[Table 1, about here]

Netnographic analysis and results

The unit of analysis of the netnography is the solvers' discussion. To analyze the 54 relevant discussions, we used the software NVivo8 and, following the procedure applied by previous scholars (e.g., Bauer et al., 2016; Divakaran, 2017), open and axial coding procedures were followed to identify fairness factors from the data (Strauss and Corbin, 1990).

Using an open coding scheme (Strauss and Corbin, 1990), the two authors inductively identified the first-order concepts, assigning a code to each discussion. To guarantee consistency and uniformity in the open coding procedure, we developed a preliminary list of codes by reading 10 discussions, together, and defining common rules for assigning codes (Weber, 1985). For instance, on reading the following discussion titled "Increase prize for 3D contests" we realize that solvers are worried about being underpaid for developing a design:

> "I see more and more 3D designers joining 99designs, but also, more and more of them are quitting. Main reason is we, 3D designers are underpaid for our job, and prizes on contests here are far too low than they should be. At first chance to earn some serious money, every designer will leave this forever. […] I tried several freelancing communities and to be honest, only 99designs suits me fine, but that's not good reason to stay here when I can't earn some decent money and be payed fairly for job I'm doing".

. Moreover, recognizing the solvers' feeling of underpayment as a fairness-related topic, the two authors agreed to assign the code "Underpayment feelings" to such discussions. Afterward, by using the preliminary list of codes, the two authors independently read and coded the remaining discussions and, where necessary, integrated the list with additional codes. The open coding procedure has an overall rate of agreement between the two authors of 87% and the coding differences were discussed to reach a consensus. The codes resulting from the open coding are reported in Table 2 together with some representative quotations that support the reasoning followed by the authors.

Then, the axial coding procedure was performed to group the codes that emerged from the open coding procedure (Strauss and Corbin, 1990). Particularly, the two authors recognized the common characteristics among the codes and then aggregated and synthesized such characteristics into second-order dimensions. The second-order dimensions represent the fairness factors that solvers care about. For example, considering the codes “Accessing ratings assigned by seekers”, “Comparing the quality of the solution proposals” and “Infringements reporting” we can identify that the solvers’ discussions about these three codes are related to the blindness of contests. In fact, in a non-blind contest, the ratings assigned by the seeker to the solution proposals are available to everyone, all the solution proposals are visible throughout the competition, and solvers can report potential violations of property rights. Thus, identifying the blindness of a contest as the fairness factor behind the three aforementioned codes, the two authors agreed on grouping them under the second-order concept “Non-blind”. The axial coding procedure was performed by the two authors independently. In this second step, the two authors had an overall agreement rate of 83% and the coding dissimilarities are discussed to find an agreement. As a result of the axial coding procedure, the two authors identified three different fairness factors, namely prize award, award guaranteed, and non-blind.

Table 2 summarizes the netnography results obtained through the procedure described above. Moreover, Table 3 reports the number of relevant discussions related to each identified fairness factor.

[Table 2 and Table 3, about here]

THEORETICAL BACKGROUND

Organizational justice and fairness theory in the idea crowdsourcing context

Organizational justice and fairness theory has been largely used to describe the role of fairness in a workplace (e.g., Barling and Phillips, 1993; Simmers and McMurray, 2018). Previous literature suggests that fairness theory may explain a wide range of employees’ attitudes and behaviors such as organizational commitment, creativity, willingness to collaborate and take risks, organizational identification, and job satisfaction (e.g., Rupp et al., 2017; Zou et al., 2015). Since idea crowdsourcing platforms constitute a new kind of workplace where solvers (employees) self-select for a contest (job application) designed by a seeker (employer), organizational justice and fairness theory seems the appropriate lens to investigate the solvers' behaviors and, in particular, their self-selection (Franke et al., 2013; Fieseler et al. 2019).

Organizational justice scholars suggest that fairness concerns the perceptions of justice about the outcomes that an employee receives (Adams, 1965; Colquitt, 2001). In the idea crowdsourcing context, fairness perceptions about the outcome arise from solvers' assessment concerning whether the reward they could gain from participating in a contest is fair or not (van den Bos et al., 1997; Feller et al., 2012; Gilliland, 1993). The reward depends on the financial gains and the possibility for solvers to benefit from some other non-financial advantages, such as improving their skills and signaling their reputation (Ye and Kankanhalli, 2017). When assessing the fairness of a contest, solvers evaluate the equity between the reward they could gain (outcome) and the effort they are supposed to expend in solving the problem (input) (Greenberg, 1990; Simmers and McMurray, 2018). Then, solvers compare such an outcome-to-input ratio with that of different referent parties (Adams, 1965; Rupp, 2017), such as another solver participating in different contests, themselves participating in different contests, and the seeker broadcasting the problem. When these outcome-to-input ratios are balanced, that is the reward properly compensates their effort, solvers perceive the contest as fair (Colquitt et al., 2005; Deutsch, 1975; Fieseler et al., 2019). Conversely, when the assessment of the outcome-to-input ratio reveals disparities because, for example, solvers feel that the seeker undervalues their work or is making a fortune from a cheaply rewarded winning solution, solvers develop perceptions of unfairness (Franke et al., 2013; Greenberg, 1990). Feelings of unfairness may result from both over-compensation and under-compensation, however, it is commonly recognized that in the crowdsourcing context solvers are unlikely to develop perceptions of unfairness for receiving rewards that exceed their effort (Adams, 1965; Cropanzano et al., 2003; Franke et al., 2013).

Moreover, organizational justice and fairness theory scholars have recognized that perception of fairness can also regard the procedures and rules regulating the process that lead to the allocation and distribution of the outcomes to employees (Gilliland, 1993; Leventhal, 1980). In idea crowdsourcing contests, solvers' perceptions of fairness may be related to the procedures and rules regulating the winning solutions' selection process (Gilliland, 1993; Rupp et al., 2017; Franke et al., 2013; Fieseler et al., 2019). Solvers develop fairness perceptions when the procedures chosen by the seeker to regulate the selection of the winning solution embody certain normatively accepted principles (Leventhal, 1980; Sheppard and Lewicki, 1987). Particularly, when the evaluation of the solution proposals reflects the principle of equity among different solvers and whether the selection of the winning solution follows the accuracy, transparency and impartiality criteria, solvers will perceive the contest as fair (Franke et al., 2013; Di Gangi et al., 2010; Leventhal, 1980). Also, perceptions of fairness arise whether the winning solution selection process is corrigible, implying that solvers have the opportunity to detect and correct possible seekers' inaccurate decisions in the allocation of the award (Leventhal, 1980; Sheppard and Lewicki, 1987). In turn, if the procedures and rules regulating the winning solutions' selection process do not embody the aforementioned normative principles and are not corrigible by the solvers, they are perceived as unjust, leading the solvers to experience feelings of unfairness (Cohen-charash and Spector, 2001; Fehr and Schimidt, 1999).

Hypotheses development

In line with the organizational justice and fairness theory (e.g., Leventhal 1980; Gilliland, 1993; Cohen-Charash and Spector 2001), we reason that the three factors emerging from the netnography, i.e., *Prize Award*, *Award Guaranteed* and *Non Blind*, can be framed as factors that intervene in the solvers' perceptions of fairness because they are related to the reward a solver could gain from participating in a contest and to the procedure regulating the winning solution selection process. Since fairness perceptions affect solvers' emotions (e.g., experiencing anger, happiness, pride, disappointment, or frustration), cognitions (e.g., cognitively distorting inputs and outcomes of themselves or others) and, eventually, behaviors (e.g., performance, participation, commitment or withdrawal) (Adams, 1965; Cohen-Charash and Spector, 2001), we argue that the three aforementioned fairness factors act as antecedents guiding seekers in self-selecting for participating in idea crowdsourcing contests.

Considering *Prize Award,* this represents the amount of money a solver can gain from winning a contest. The solvers' considerations about the monetary prize involve the solvers' assessments concerning whether what they could gain from winning an idea crowdsourcing contest compensates for their time and effort (van den Bos et al., 1997; Feller et al. 2012). Particularly, it has emerged from the solvers' discussions in the 99designs blog that, when debating about the equity of the prize award, solvers make a comparison between the money the seeker will pay to acquire the winning design and the effort of the solver who has submitted it. Depending on the amount of the prize, solvers perceive whether or not their work and effort are fairly remunerated. Particularly, the higher the amount of money that solvers could gain, the more likely they are to develop perceptions of fairness. This result is in line with Franke et al. (2013), suggesting that the monetary prize represents a potential outcome for solvers, and it affects the solvers' perceptions of fairness because it impacts their outcome-to-input ratio.

When solvers develop fairness perceptions about the amount of the monetary award, they will feel treated fairly and will be more likely to engage in the competition (Simmers and McMurray, 2018). Conversely, when the monetary prize would not compensate solvers for the effort they put in solving the problem, they will perceive unfairness (Franke et al., 2013; Zou et al., 2015). When solvers develop perceptions of unfairness, they will alter their behavior to fix the balance in the outcome-to-input ratio by performing equity-restoring actions, meaning that they pursue behaviors that might damage the seeker and make the outcome-to-input ratio less negative from their perspective (Greenberg, 1990). These actions include adjustments in the solvers' input that can range from decreasing their effort in solving the problem to the avoidance of participating in the contest (Greenberg and Scott, 1996). Thus, also in line with previous crowdsourcing literature (i.e., Franke et al., 2013), we propose that the prize award influences the self-selection process. Particularly, when the prize award is perceived as fair, solvers are more likely to be incentivized to participate in that contest. When the prize award is perceived as unjust, solvers will develop feelings of disapproval and aversion that negatively affect their decision to self-select for that contest. Consequently, the first hypothesis of the study is:

H1. Higher prize awards positively impact the solvers' self-selection.

Focusing on the *Award Guaranteed*, this represents an assurance for solvers that the seeker will pay-out the monetary award at the end of an idea crowdsourcing contest even if she/he has not found a suitable solution (Wooten and Ulrich 2017). By promising the pay-out of the award, the seeker can prevent solvers from feeling exploited and exposed to free-riding behaviors (Deng et al., 2016; Foege et al., 2019). Particularly, the solvers' discussions in the 99designs blog highlight that solvers are concerned about the possibility that seekers, falsely claiming they did not find a suitable solution, ask for a refund and obtain their money back from the platform without allocating the monetary prize. In such a circumstance, solvers can perceive that the effort they put in to generate solutions will increase the outcome for seekers instead of themselves, thereby generating a disequilibrium between solvers and seekers' outcome-to-input ratios (Adams, 1965; Jian et al. 2019). Conversely, assuring the pay-out of the award reduces the uncertainty related to seekers' behaviors (Jian et al., 2019) and positively affects the solvers' perceptions of fairness. By guaranteeing to pay-out the prize, indeed, seekers make a commitment to solvers based on expectations of future benefits and gains they might eventually capture at the end of the contest (Jokela and Söderman, 2017). Under such a circumstance, the outcome of the solver is guaranteed while that of the seeker is not, because seekers may not find a suitable solution. Thus, guaranteeing the award makes the outcome-to-input ratio of the solver more favorable compared to that of the seeker, leading solvers to develop perceptions of fairness.

When solvers develop fairness perceptions about the commitment of the seeker in paying-out the award, they will feel treated fairly and will be more likely to engage in the competition (Simmers and McMurray, 2018). Conversely, when seekers are not committed to guaranteeing the award, solvers will develop perceptions of unfairness. In this scenario, solvers will alter their behaviors to restore the balance of the outcome-to-input ratio, pursuing actions that aim at damaging the outcome of the seekers and make their own outcome more favorable (Greenberg, 1990). For example, solvers may decrease their effort in solving the problem or avoid participating in a contest at all (Greenberg and Scott, 1996). Thus, we argue that also the award guaranteed influences the self-selection of solvers. In particular, we advance that when the prize award is guaranteed, solvers are more likely incentivized to self-select in a contest. When the award is not guaranteed, solvers will develop feelings of unfairness, which negatively affects their decision to participate in a contest. Accordingly, the second hypothesis of the study is:

H2. Award guaranteed positively impacts the solvers' self-selection.

Considering *Non-blind*, this shapes the circumstances under which the solutions submitted by solvers and the ratings and feedback that seekers assign to these solutions are visible and available to everybody throughout the competition (Wooten and Ulrich, 2017). From discussions in the 99designs blog it has emerged that by comparing the quality of the solutions submitted by others with their designs and accessing the rating assigned by seekers, solvers will perceive there is no favoritism or issues related to the possibility that some unqualified solvers have backing to unfairly win the contest when submitting poor quality designs. Indeed, sharing their feedback and ratings during the competition, seekers reveal their opinions on the solutions and reduce solver uncertainty concerning the evaluation criteria adopted to assess such solutions (Cohen-Charash and Spector, 2001; Jian et al., 2019). This situation reflects that the transparency of a contest and the impartiality of seekers represent desirable attributes (Di Gangi et al., 2010; Bauer et al., 2016) affecting solvers' perceptions of fairness concerning the procedure and rules regulating the selection of the winning solution. Moreover, the 99designs blog discussions highlight that non-blind contests allow solvers to develop a sense of fairness because they can monitor and intervene in the selection of the winning solution. By accessing all the solutions submitted during contests, solvers can intervene in the winning solution selection process by reporting possible deceptions and intellectual property rights infringements, such as theft and imitation of solutions among solvers, thereby avoiding dishonest solvers being selected as winners (Bauer et al., 2016; Di Gangi et al., 2010; Nambisan and Baron, 2010). Thus, allowing solvers to have an active role in the selection process of the winning solution, non-blind contests lead solvers to develop perceptions of fairness (Leventhal, 1980; Sheppard and Lewicki, 1987).

To the extent that solvers perceive the seekers' evaluations and winning solution selection process as fair, solvers will develop a sense of partnership toward the seekers

(Korsgaard et al., 1995; Li et al. 2007). Such a sense of partnership constitutes a critical motivating factor since it leads solvers to identify themselves as part of the seeker organization and so to make their time, skills and experiences available to the seeker participating in their contests (Faullant et al., 2017; Kim and Mauborgne, 1993; Nambisan and Baron, 2010). In turn, when the contest is blind, solvers perceive that the procedures of the contest are unfair because, for example, they believe that the seekers favor some solvers over others or they are hindered to intervene and correct inaccurate seekers' decisions, thus, solvers will feel disregarded and in a marginal position within the seekers' creativity and innovation process (Li et al., 2007). Developing these negative feelings discourages solvers to work in favor of the seeker and will lead them to undertake behaviors that restore the fairness within the seeker-solver relationship (Alexander and Ruderman, 1987; Li et al., 2007; Masterson et al., 2000). Such restoring behaviors can range from reducing the quality of their contributions in solving the problem to avoiding participating in the contest and moving, for example, to a contest broadcast by another seeker (Franke et al., 2013; Konovsky and Cropanzano, 1991; Korsgaard et al., 1995). Thus, we argue that the blindness of a contest influences the self-selection of solvers. Specifically, when the contests are non-blind, solvers will likely increase their willingness to self-select for that contest. In turn, when the contests are blind, negative attitudes and conflict may arise that negatively affect the solvers' decisions to participate in that contest. Accordingly, we state the third hypothesis of the study:

H3. Non-blind contests positively impact solvers' self-selection.

ECONOMETRIC ANALYSIS

Empirical setting

Collecting a vast pool of knowledge and skills from both professional and amateur designers (solvers), this platform seems the appropriate setting also for conducting the econometric analysis of this study. Indeed, at the end of each contest, 99designs publishes possible measures of solvers' self-selection, such as the number of designers that participated in the contest and the number of solutions submitted (Sun et al., 2015). Moreover, the problem statements of the 99designs contests describe the attributes of the problem; this also includes information about the monetary award and the rules regulating the selection of the winning solution (Lüttgens et al., 2014; Mazzola et al., 2018).

Sample and measure

The contest is the unit of analysis of the econometric investigation. We collected secondary data from the problem statements of contests broadcast from January to October 2014. Since the 99designs platform does not have an archive collecting the contests broadcast, during each day of the data collection period (270 days) we randomly selected a sample of five contests. The initial sample consisted of 1350 contests. From this sample, we removed those contests withdrawn before the end date because it is not possible to collect data about the number of self-selected solvers. The final dataset contained 1067 contests, arranged as cross-sectional as each observation is set at the due date.

Following previous crowdsourcing literature (e.g., Terwiesch and Xu 2008; Jeppesen and Lakhani 2010; Boudreau et al., 2011) we operationalized the dependent variable as a count variable, *Self-selected solvers*, measuring the number of solvers that submitted at least one solution to the contest.

Concerning explanatory variables, *Prize award* is a continuous variable that measures the amount of money that the winning solver will receive at the end of the contest. Moreover, we operationalized *Award guaranteed* through a dichotomous variable that is 1 if the seeker decides to guarantee to payout the prize at the end of the contest even if she/he has not found a suitable design, 0 otherwise. Finally, *Non-blind* is a dichotomous variable assuming the value 1 if the solution proposals submitted to that contest are visible to everyone during the competition, 0 otherwise.

We also include some control variables in the analyses. First, we control whether the seeker reveals her/his identity when broadcasting the contest using the dichotomous variable (e.g., Pollock et al., 2019), *Seeker identity*, which is 1 if the seeker discloses her/his identity to the solvers, 0 otherwise. Moreover, we include the variable *Seeker typology* to control the effect of different seekers' typology on the solvers' self-selection. *Seeker typology* is operationalized through four dummies representing the different typologies of seekers: 'Firm', 'Private', 'Non-profit', and 'Unknown'. To control for the influence that the *Duration* of the competition has on the number of self-selected solvers, we include the natural logarithm of the number of days between the beginning and deadline of a contest (e.g., Bockstedt et al., 2016). Furthermore, we control for the level of *Competition* that characterizes the idea crowdsourcing contests. Particularly, since the level of competition of a contest depends on the quality of the participants (Shao et al., 2012; Li and Hu, 2017), we operationalized the variable *Competition* as a continuous variable measuring the average rating of the solvers that participate in a contest (ranging from one to five stars). Furthermore, to understand the impact that each *Contest type* has on the solvers' self-selection, we also controlled for the different categories of contests. Particularly, following the classification of the 99designs platform we operationalized the variable *Contest type* by using four dummy variables ('Logo', 'Website & Application', 'Art, Book & Merchandising', and 'Packaging & Advertising'). Finally, through ten dummies ('January', 'February', 'March', 'April', 'May', 'June', 'July', 'August', 'September', and 'October') we checked for the effect that the *Month* in which the challenge was broadcast had on the solvers' self-selection.

Table 4 reports the descriptive statistics of all the variables.

[Table 4, about here]

Model specification

We chose the most appropriate econometric model through an in-depth analysis of the data. The dependent variable *Self-selected solvers* is a count variable that takes only discrete, non-negative and integer values. Count data are usually analyzed with the Poisson regression in which over-dispersion is a likely downside (Hausman et al., 1984). We ran several tests to control for over-dispersion (Salter et al., 2015). First, we assessed the goodness-of-fit (gof) test to assess the Poisson assumption alongside the negative binomial model. Since the value for chi-square in the gof test (model 1: $\chi 2 = 37956.38$, $p = .000$) is significant, this means that the Poisson distribution is not the appropriate model. As a double-check we triangulated the gof test result with the likelihood ratio test, a test of the over-dispersion parameter alpha included in the negative binomial regression output. Alpha is significantly different from zero (chibar2 = 1.9e+04 p =.000) and this strengthens previous results that Poisson distribution is not suitable for our data. Therefore, we chose the negative binomial model for our analysis.

Results from the econometric analysis

Table 5 reports the correlation values of all the variables. Even though the pairwise correlation assessment did not disclose any criticalities, we calculated a more powerful measure of multicollinearity, namely the variance inflation factor (VIF) (Stevens, 1996). The VIF coefficients were all below the critical value of 10, so the explanatory variables could be included in our models simultaneously (Gujarati, 2004).

[Table 5, about here]

Table 6 shows the regression results. Model 1 includes only the control variables and operates as a baseline model. Models 2 and 3, respectively, introduce the explanatory variables *Prize award* to test H1 and *Award guaranteed* to test H2. Model 4 includes the explanatory variable *Non-blind*, to estimate H3. Finally, Model 5 assesses the full model considering all the explanatory variables. Table 6 also reports the likelihood ratio tests' values to show the improvement of the model fit when evaluating the full models.

[Table 6, about here]

Regarding the control variables, *Seeker identity* is not significant in Model 1 meaning that the self-selection process is not affected by the seekers' decision to reveal their identity. Also, the dummy variables related to *Seeker type* are not significant meaning that, when deciding whether to self-select in a contest, solvers are not influenced by the typology of the seeker. Moreover, Model 1 shows that the dummies indicating the *Contest type* are all significant suggesting that 'Logo' contests attract a higher number of solvers respective to 'Art, Book and Merchandising' contests (omitted as a baseline category), whereas 'Packaging & advertising' and 'Website & application' contests attract fewer solvers. Furthermore, the level of *Competition* of a contest has a significant and negative impact on the number of *Self-selected solvers*, suggesting that solvers are discouraged from participating in a contest in which the other participants are highly competent and skilled and have a consolidated reputation in the community of the crowdsourcing platform. Moreover, since the *Duration* of the contest has a significant and positive effect on the number of *Self-selected solvers*, the results suggest that a long-lasting contest may attract more solvers. Finally, some dummy variables related to the *Month* are significant ('June' has a significant and positive coefficient, whereas August has a significant and negative coefficient), this means that the period of the year during which the contest was broadcast influences the number of self-selected solvers.

Concerning the explanatory variables, in Model 2, the coefficient of *Prize award* is significant and has a positive effect on *Self-selected solvers*, thus supporting H1. Since in Model 3 the coefficient of *Award guaranteed* is significant and positive, we found confirmation for H2. Moreover, Model 4 shows a positive and significant coefficient of Non-blind, thus corroborating H3. The inclusion of all of the explanatory variables in Model 5 further confirms all the hypotheses of the study.

Robustness checks and endogeneity

Several additional analyses were carried out to check the robustness of previous results. First, we assessed the hypotheses by using an alternative dependent variable, *Submitted ideas*, which measures the total number of designs submitted into a contest. The results of this additional analysis, which are reported in Table 7, are consistent with those obtained with the variable *Self-selected solvers* (Table 6).

Second, we conducted further analyses to assess the relationship between the three fairness factors and the solvers' self-selection in the case of multiple submissions. Indeed, in the 99designs crowdsourcing platform, solvers are allowed to submit more than one solution proposal in the same contest. From the seekers' standpoint, allowing solvers to submit multiple solution proposals is convenient because receiving higher quantities of ideas is associated with a greater probability of receiving suitable, high-quality solutions (Jeppesen and Lakhani, 2010; Terwiesch and Xu 2008). Moreover, the allowance of multiple submissions is a desirable contest's attribute also considering the solvers' perspective. Indeed, by making multiple submissions a solver is more likely to succeed in a contest since she/he can try out different ideas and make adjustment considering the feedback and the new information which emerges during the competition (Bockstedt et al., 2016; Simonton, 2003). Thus, we reasoned that the three fairness factors should increase the effort a solver dedicated to the competition in terms of the number of submissions. For performing this additional analysis, we used the variable *Multiple submission,* which is operationalized as a continuous variable measuring the average number of solution proposals submitted by the solvers participating in a contest. The results of this further analysis are shown in Table 8. Particularly, the results suggest that the three fairness factors have a significant and positive effect on the *Multiple submission* suggesting that higher prize award, guaranteed award and non-blind competition increase the effort a solver puts into solving seekers' creativity and innovation problems.

Third, we checked for endogeneity concerns in our study by following Echambadi et al. (2006). Endogeneity problems occur when explanatory variables are not independent of the error term. Factors that can cause endogeneity concerns are simultaneity/reverse causality, measurement errors and omitted variable bias (Wooldridge, 2002). Because of our theorizing, simultaneity/reverse causality is not an issue, since the seekers' decisions about the award and the procedures regulating the winning solution selection process precede the self-selection of solvers. On the other hand, omitted variables may be a real concern in our models. For example, critical seekers' decisions related, for example, to the allocation of IPR could affect the process of solvers' self-selection (e.g., Mazzola et al. 2018). Omitting variables that are not available in the 99designs platform represents a significant issue in the econometric analysis since it may lead to overestimation of the impact of our explanatory variables *Prize award*, *Award guaranteed* and *Non-blind* on the dependent variable *Self-selected solvers*. To effectively address endogeneity concerns we applied the instrumental variables (IV) method (Hamilton and Nickerson, 2003; Wooldridge, 2002). This method aims to isolate the endogenous part of the explanatory variables to examine their true causal effect on the dependent variable. In our case, we aim to separate the endogenous part of our three explanatory variables to estimate their actual effect on the *Self-selected solvers* by using other variables (i.e., the instruments), which predict the explanatory variables, but not the dependent variable. Specifically, we chose two different instruments, *Seeker experience* to predict the explanatory variables *Prize award* and *Award guaranteed* and *Non-Disclosure Agreement* (*NDA*) to predict the explanatory variable *Non-blind*. Through a dichotomous variable assuming a value of 1 if the seeker has previous experience in designing crowdsourcing contests, 0 otherwise, the first instrument *Seeker experience* evaluates whether the seeker has broadcast one or more contests in the platform. We chose this instrument since, if the seeker has broadcast previous contests, she/he is abler in evaluating the solvers' effort required to solve a problem and setting an appropriate award. We followed the Plourde et al. (2014) procedure to check the validity of this instrument; *Seeker experience* significantly and positively affects *Prize award* (β=47.8 with p-value=0.018) and *Award guaranteed* (β=2.78 with p-value=0.000) while *Self-selected solvers* does not (p-value=0.20). The second instrumental variable, *NDA*, measures whether, before participating in a contest, solvers have to sign a non-disclosure agreement, i.e., a contract that officially sets rules about sharing information (Hannah and Robertson, 2015; Witman, 2005). In the crowdsourcing context, the seeker may have important information to reveal to solvers submitting a solution but not to other third parties. Since the *NDA* imposes confidentiality on solvers, it can be considered a measure of information transparency (Zogaj et al., 2014). The *NDA* is a binary variable assuming a value of 1 if the seeker decides to engage in a confidential relationship with the solvers that participate in her/his challenge, 0 otherwise. We checked for the validity of the *NDA*. Also, this second instrument is valid since it significantly impacts *Non-blind* and shows a negative coefficient (β=-0.57 with p-value=0.000) but it does not influence *Self-selected solvers* (p-value=0.25).

Once the instrumental variables were validated, we applied a two-stage regression approach (Hamilton and Nickerson, 2003; Wooldridge, 2002). Firstly, we regressed the explanatory variables on their respective instrumental variables. The resulting fitted values were then used in the second stage (i.e., in the main models) instead of the endogenous variables. From this additional analysis, we obtained confirmation about the results shown in Table 6 (i.e., *Prize Award* $\beta=0.5$ with p-value<0.01; *Award guaranteed* $\beta=0.93$ with p-value<0.05; *Non-blind* $\beta=1.84$ with p-value<0.05), relaxing the endogeneity concerns while providing consistency and validity to our previous results (full table results of endogeneity analysis are available from the authors upon request).

DISCUSSION AND CONCLUSIONS

While the idea generation contest has been acknowledged as a tool that can be utilized for innovative ideas, few studies address how seeker firms can use fair idea generation contests to attract large pools of solvers (e.g. Franke et al., 2013). Our research offers a better understanding of contest design and solvers perception of fairness in their decision to participate in the idea crowdsourcing contests. Specifically, the study investigated how seekers' decisions, related to the design of contests, influence solver participation by affecting their perceptions of fairness. By iterating between our empirical findings and existing theory, drawing distinctively on the literature (i.e., organizational justice and fairness theory and crowdsourcing literature) to develop a consistent line of argument, we believe that our study offers a deeper understanding of fairness in crowdsourcing contest. Firstly, netnographic analysis leveraging on qualitative data gathered from the 99designs crowdsourcing platform was performed. The empirical insights from the netnography showed evidence concerning three further factors that shape the concept of fairness in a real crowdsourcing context. We found that the amount of the monetary prize can induce solvers to develop perceptions of fairness. We also observed that guaranteeing the payout of the monetary award at the end of the contest can lead solvers to develop perceptions of fairness. Moreover, we found that the blindness of a contest can affect solvers' perceptions of fairness. Then, we built a distinctive dataset of 1067 contests broadcast on 99designs and performed an econometric analysis to examine the impact of three fairness factors on the solvers' self-selection.

Findings from the econometric analysis showed that, as hypothesized, the three aforementioned fairness factors have significant impacts on the solvers' self-selection process. The first hypothesis argued that when the monetary award is perceived as fair, solvers are more likely to be incentivized to participate in that contest. We found confirmation for this hypothesis since the findings show that increasing the amount of the monetary award has positive effects on the self-selection of the solvers. These results confirm the relationship between outcome issues and fairness: people generally respond positively to more favorable outcomes (Adams, 1965). In line with previous crowdsourcing literature, this result reveals that solvers care about the equity of resource distribution and they perceive that their efforts will be fairly remunerated with a higher award (Franke et al., 2013).

The second hypothesis argued that assuring solvers the payout of the monetary award increases their willingness to participate in that contest. Our findings also confirm this hypothesis, suggesting that contests in which the award is guaranteed are more attractive than those characterized by a non-guaranteed award. This result suggests that since solvers consider earning money is a critical reason to participate in a contest, they are concerned about the uncertainty of their outcomes and look favorably on the commitment of the seeker in paying out the prize at the end of the contest (Jian et al., 2019). The award guaranteed fairness factor, by signaling to solvers that the seeker is reliable and committed to paying out the prize at the end of the challenge, boosts the solvers' self-selection process.

The third hypothesis highlighted that unblind contests are perceived as fair and, thereby, increase solvers' willingness to self-select for that contest. The results support the idea behind our investigation that, in contests, solvers also have concerns about the process regulating the selection of the winning solution. We found that non-blind contests positively impact the self-selection of solvers, suggesting solvers prefer contests in which they can control the selection process and evaluate the solution proposals. This result is in line with Cohen-Charash and Spector's (2001, p. 280) research indicating that '*solvers create their fairness judgments with regard to their beliefs of how the systems or procedures "should" operate*'. Thus considering that, in a non-blind contest, solvers can assess the solution proposals submitted by others and the evaluation of seekers on these proposals, and intervene in the winning solution selection process, solvers perceive non-blind as a fairness factor desirable to join a contest.

Contribution to literature

The results of this research offer several contributions to previous crowdsourcing literature. Contrary to previous studies that basically take a solver's perspective in explaining the challenge performance related to fairness (e.g. Franke et al., 2013; Zou et al., 2015; Faullant et al., 2017; Fieseler et al. 2019), in this research, we adopt a seeker's perspective. We suggest that seekers should effectively design the knowledge creation process in a crowdsourcing contest by maintaining high levels of solvers' motivation and fairness perception during the challenge. In fact, despite a great part of a crowdsourcing task being done outside of the seeker company, the seeker has to dedicate resources and should not neglect its efforts throughout the process. In doing so, seekers may participate in successful crowdsourcing experiences. Furthermore, we evaluate fairness perception through real data as well as an *ex post* analysis rather than an *ex ante* judgment. In particular, we measure the participation of the challenge as the number of solvers that actually self-select in that challenge by submitting an idea. In this sense, differently from Franke et al. (2013) that have considered the fairness effect of willingness to participate, in our study, we analyze fairness as actually experienced by the solvers rather than only being anticipated as an ex-ante judgment. In addition, we tested our theoretical framework by using archival data based on real challenge data. Besides the typical limitations of archival data, these are objective numbers and tell exactly how the crowdsourcing system behaves. Differing from previous empirical studies on crowdsourcing (Terwiesch and Xu, 2008; Faullant et al. , 2017, Franke et al., 2013; Zou et al. 2015), since archival data are not subjective and there is no experimenter- or survey-imposed bias on them, we are able to investigate the role of fairness in attracting solvers in a real setting with real players that invest real money and real effort. Hence, using data on actual behaviors based on a distinctive dataset of 1067 contests enriches the external validity of our results. In sum, we believe previous studies could not capture the whole picture of fairness in crowdsourcing, whereas our study offers a more complete and realistic representation of how fairness influences idea generation contests.

Second, despite previous scholars have already investigated the topic of fairness in the crowdsourcing context (e.g. Faullant et al. , 2017, Franke et al., 2013; Zou et al. 2015), the set of fairness factors highlighted by their researches cannot be considered exhaustive because of the complex nature of the concept of fairness. As largely recognized by organizational justice and fairness scholars (e.g., Brady and Dunn, 1995; Colquitt, 2001; Cropanzano et al., 2015), fairness is a multidimensional concept shaped by several facets which can take on diverse meanings and definitions in different contexts. The peculiarities of fairness have pushed fairness scholars to engage continuously in further assessment and reconceptualization of such a concept (e.g., Rupp et al., 2017). Inspired by the same spirit we then aimed to further explore the concept of fairness in the crowdsourcing context looking for new elements, which may enrich the debate around fairness in this setting. Highlighting that there are further elements shaping solvers' perceptions of fairness, our results add new interpretations to the fairness concept in the relationship between seekers and solvers. In particular, this study adds to previous literature by suggesting that, alongside the fairness factors already recognized by previous scholars, and beyond the prize of the contest, solvers also consider as fairness mechanisms the commitment of the seeker in guaranteeing the award and the blindness of the contests.

Third, we provide contributions to the crowdsourcing literature investigating how seekers can intentionally boost the solvers' self-selection process through the design of the contest (e.g., Boudreau et al., 2011; Erat and Krishnan, 2012; Mazzola et al., 2018; Pollok et al., 2019). A major area that should drive future research effort is that of attracting, managing and retaining the crowd of solvers. As Boudreau and Lakhani (2013) argue, crowds have been around for centuries but, today, the internet can connect communities of people with different profiles and direct their energies toward problems in a possibly concerted way. However, the crowd will be active in taking on and solving tasks only as long as they are meaningful for them, so the problems, the coordination mechanisms and the fairness mechanism should be designed accordingly. Previous literature identifies several contests' attributes that seekers can leverage as tools for pushing solvers to participate in their contests such as the formulation of the problems (e.g., Zheng et al., 2011; Pollock et al., 2019), the amount and structure of the award (e.g., Erat and Krishnan, 2012; Franke et al., 2013), the use of a feedback system (e.g., Wooten and Ulrich, 2017), the use of trust mechanisms, such as the disclosure of the seeker's identity (e.g., Garcia Martinez, 2017; Pollock et al., 2019), and the arrangement regulating the management of the intellectual property rights of the winning solution (e.g., Mazzola et al., 2018). Seekers set such contests' attributes when designing the crowdsourcing contests and include information about the design of the contest in the problem statement (de Beer et al., 2017; Mazzola et al., 2018; Pollok et al., 2019). The problem statement represents the only means of communication between seekers and solvers before the beginning of the competition, and it is used by solvers to search for clues that may reduce their uncertainty concerning whether the seeker will treat them fairly or not (Lüttgens et al., 2014; Pollock et al., 2019). When developing their perceptions of fairness, solvers decide whether to self-select in that contest (Franke et al., 2013). Thus, the design of the contest is a key activity for seekers aiming to live up to the expectations of solvers and encourage them to participate (Bullinger et al., 2010; Zheng et al., 2011). As such, our research complements earlier studies concerning how to attract solvers through the design of the contest behaving fairly. We suggest that, alongside all the already recognized contests' attributes, when designing contests, seekers should include information about their commitment to treating the solvers fairly by setting appropriate prize awards, guaranteeing the payout of the award and organizing non-blind competitions.

Finally, our results offer insights into the crowdsourcing literature that focuses on the value capturing discourse (Afuah and Tucci, 2013; Chesbrough et al., 2018; Fedorenko et al., 2017; Kohler and Nickel, 2017). While a large part of this literature mainly tackles the value capture question, considering how seekers can take advantage of crowdsourcing and capturing value from the crowd, it is recognized that the solvers also need to capture value from participating in crowdsourcing contests (Fedorenko et al., 2017; Kohler and Nickel, 2017). However, it may be difficult to simultaneously satisfy the value-capturing needs of both seekers and solvers because they usually pursue dissimilar goals (Gefen et al., 2016). On one hand, when organizing idea crowdsourcing contests, seekers want to fulfill their creativity and innovation needs through relatively cheaper and quicker access to a wide number of innovative and creative solvers' ideas (Conley and Tosti-Kharas, 2014; Howe, 2006; Natalicchio et al., 2017). On the other hand, solvers generally participate in idea crowdsourcing contests to earn money, improve their skills and abilities and, even, to have fun (Boons et al., 2015; Ye and Kankanhalli 2017). In this context, our findings suggest that fairness allows both seekers and solvers to fulfill their value capturing needs. Considering the seekers' perspective, fairness can enhance the possibility of fulfilling their innovation and creativity needs, attracting a higher variety of external individuals into their activities (Franke et al., 2013). On the other hand, concerning the solvers' point of view, fairness can satisfy their expectations about the reward and their needs for feeling pride and being respected when contributing to the seekers' innovation and creativity processes (Boons et al., 2015; Schlagwein et al., 2019; Ye and Kankanhalli, 2017). As such, motivating solvers to self-select and promising them the ethics of the contest, our research suggests fairness acts as the means to align seekers and solvers' objectives by balancing the value-capture between them.

Managerial implications

Our research provides several implications for managers organizing idea crowdsourcing contests. Generally, our results indicate the importance of designing a contest perceived by solvers as fair to boost the solvers' self-selection process.

Managers of seeker companies need to be aware of the perception of fairness solvers develop concerning the award and rules regulating the selection of the winning solution. Specifically, to attract a large pool of solvers, managers might design appropriate awards balancing the effort solvers put into developing their solutions and the money they will receive. Furthermore, managers should design specific reward mechanisms to increase the solvers' level of trust and their sense of partnership with the seeker company. For example, by assuring that they will payout the award at the end of the contest, seeker companies can attract a larger number of solvers. Moreover, the promise of a clear, straightforward and transparent crowdsourcing process that reflects the equity and accuracy principles can increase the solvers' willingness to participate in a contest. This assurance can be attained, for example, by including non-blind clauses. When solvers can look at the solutions proposed by other designers they can also access the seekers' feedback and suggestions regarding those submissions. Thus, by comparing their proposals with those submitted by others, solvers can evaluate the system of judgment that the company will use in selecting the winning solution, thereby increasing their fairness perceptions. Moreover, designing a non-blind contest seeker companies allow solvers to participate in the selection process by monitoring the behaviors of others and reporting possible unfair behaviors such as intellectual property rights infringements. This allowance enables the solvers to develop a sense of partnership toward the seeker companies and increases their willingness to collaborate in their innovation and creativity process.

To harness beneficial reciprocities, managers must nurture the needs of solvers and the creative diversity embedded in solvers, while simultaneously extracting organizational value. If development trajectories are overly stringent without fair distribution of value, solvers are locked into providing incremental improvements to existing solutions with no willingness to participate in a contest; however, more transparent, accountable rules and procedures may attract more solvers who may develop more radical, competence-destroying solutions that are inimitable (Jeppesen and Frederiksen, 2006). Clearly, the capabilities of the solvers can enable seeker organizations to more accurately assess and appraise potential innovative ideas and opportunities if harnessed correctly based on their contest design.

Managers of the idea crowdsourcing platform have to consider the role played by a fair design of the contest in aligning seekers' and solvers' objectives. Indeed, hosting a contest that motivates solvers to participate, assuring a fair distribution of value, and promising transparency and equity in the rules and procedures is critical for the crowdsourcing platform aiming to attract seeker companies and solvers, match their needs through fair idea crowdsourcing initiatives and, so, retain them in their community. Particularly, managers of the crowdsourcing platforms should provide some recommendations to both seeker companies and solvers. When supporting a seeker company in broadcasting a contest, platform managers have to suggest to their clients that behaving fairly toward the crowd can increase the number of potential solution providers interested in solving their problems. In particular, they have to advise seeker companies to be fair and set appropriate monetary award that compensates solvers for the effort and time they expend in solving the problem. Also, the crowdsourcing platform has to suggest to seeker companies to be committed to the contest and assure the payout of the award to avoid solvers feeling they are wasting their time, thereby motivating them to participate in the crowdsourcing competition. Finally, platform managers should propose their clients increase the transparency of the contest by leveraging non-blind clauses, which allow solvers to look at the solution proposals submitted by others and report unfair behavior so that solvers can feel the winning solution selection process is unbiased and free of favoritism issues.

When sponsoring crowdsourcing contests to potential solvers, platform managers have to suggest solvers choose those contests characterized by specific attributes that can answer their fairness needs. Particularly, crowdsourcing platforms should sponsor contests characterized by higher prize awards, suggesting to solvers that these kinds of contests can compensate appropriately the effort and time they dedicate to solving the seekers' innovation and creativity problem. Moreover, the platform should suggest solvers participate in those contests that guarantee the prize award. These kinds of contests, indeed, induce solvers to feel they are not wasting their time working for a seeker who is not committed to the contest. Lastly, platform managers should advise solvers that by participating in non-blind contests they can feel part of the winning solution selection process because they can access the solution proposals submitted by others and report unfair behaviors, thereby avoiding misjudgments from seekers.

Limitations and further directions

The results and contributions of this research should be appraised considering its limitations. Our research specifically focuses on a single crowdsourcing platform for idea competitions, 99designs. While it is an appropriate context to examine the fairness issue, the findings should not be generalized to other competitions, such as challenges gathered from crowdsourcing platforms for technology competitions (e.g., InnoCentive or NineSigma). Extension of the model to different types of crowdsourcing contests will require additional field studies to examine the applicability in those contexts, such as technology contests and/or other platforms. Moreover, our research does not examine the possible causal association between different fairness factors. For example, Leventhal (1980, p. 36) proposes that perceived fairness about the procedure and rules affects the perceptions of fairness about the outcomes suggesting that 'If the procedures are seen as fair, then the final distribution is likely to be accepted as fair even though it may be disadvantageous'. Thus, future research may develop this study by examining a causal association among different fairness factors. Another possibility would be to consider the interaction between fairness factors in the crowdsourcing context (Brockner and Wiesenfeld, 1996; Greenberg, 1987). Future research should also continue to advance the fairness aspects of the crowdsourcing context, paying thoughtful consideration to issues of fairness sources and their interactions. Specifically, future research would benefit from including the relationship between the motivations of solvers and their perception of fairness of the system when the fairness and constructs of a contest's attractiveness are applied, so that each of the fairness elements has a principal equivalent.

REFERENCES

99designs. 2019. The Global Leader in Logo Design, Relocating Company Headquarters to Oakland's Uptown Neighborhood. Available at: http://en.99designs.it/about/press-releases (accessed July 2019).

Acar, O.A. (2019), "Motivations and solution appropriateness in crowdsourcing challenges for innovation", *Research Policy*, Elsevier, Vol. 48 No. 8.

Adams, J.S. (1965), "Inequity In Social Exchange", *Advances in Experimental Social Psychology*, Vol. 2 No. C, pp. 267–299.

Afuah, A. and Tucci, C.L. (2012), "Crowdsourcing as a Solution to Distance Search", *Academy of Management Review*, Vol. 37 No. 3, pp. 355–375.

Afuah, A. and Tucci, C.L. (2013), "Value Capture and Crowdsourcing", *Academy of Management Review*, Vol. 38 No. 3, pp. 457–460.

Alexander, S. and Ruderman, M. (1987), "The role of procedural and distributive justice in organizational behavior", *Social Justice Research*, Vol. 1 No. 2, pp. 177–198.

Andersen, P.H., Kragh, H. and Lettl, C. (2013), "Spanning organizational boundaries to manage creative processes: The case of the LEGO Group", *Industrial Marketing Management*, Elsevier Inc., Vol. 42 No. 1, pp. 125–134.

Barling, J. and Phillips, M. (1993), "Interactional, formal, and distributive justice in the workplace: An exploratory study", *Journal of Psychology: Interdisciplinary and Applied*, Vol. 127 No. 6, pp. 649–656.

Bauer, J. f, Franke, N. and Tuertscher, P. (2016), "Intellectual Property Norms in Online Communities: How User-Organized Intellectual Property Regulation Supports Innovation", *Information Systems Research*, Vol. 27 No. 4, pp. 724–750.

de Beer, J., McCarthy, I.P., Soliman, A. and Treen, E. (2017), "Click here to agree: Managing intellectual property when crowdsourcing solutions", *Business Horizons*, Vol. 60 No. 2, pp. 207–217.

Bockstedt, J., Druehl, C. and Mishra, A. (2016), "Heterogeneous Submission Behavior and its Implications for Success in Innovation Contests with Public Submissions", *Production and Operations Management*, Vol. 25 No. 7, pp. 1157–1176.

Boons, M., Stam, D. and Barkema, H.G. (2015), "Feelings of Pride and Respect as Drivers of Ongoing Member Activity on Crowdsourcing Platforms", *Journal of Management Studies*, Vol. 52 No. 6, pp. 717–741.

Boudreau, K.J., Lacetera, N. and Lakhani, K.R. (2011), "Incentives and Problem Uncertainty in Innovation Contests: An Empirical Analysis", *Management Science*, Vol. 57 No. 5, pp. 843–863.

Brady, F.N. and Dunn, C.P. (1995), "Business Meta-Ethics: An Analysis of Two Theories", *Business Ethics Quarterly*, Vol. 5 No. 3, pp. 385–398.

Brockner, J. and Wiesenfeld, B.M. (1996), "An integrative framework for explaining reactions to decisions: Interactive effects of outcomes and procedures", *Psychological Bulletin*, Vol. 120 No. 2, p. 189.

Brockner, J., Wiesenfeld, B.M., Siegel, P.A., Bobocel, D.R. and Liu, Z. (2015), "Riding the Fifth Wave: Organizational Justice as Dependent Variable", *Research in Organizational Behavior*, Elsevier Ltd, Vol. 35, pp. 103–121.

Bullinger, A.C., Neyer, A.K., Rass, M. and Moeslein, K.M. (2010), "Community-based innovation contests: Where competition meets cooperation", *Creativity and Innovation Management*, Vol. 19 No. 3, pp. 290–303.

Chesbrough, H., Lettl, C. and Ritter, T. (2018), "Value Creation and Value Capture in Open Innovation", *Journal of Product Innovation Management*, Vol. 35 No. 6, pp. 930–938.

Cohen-charash, Y. and Spector, P.E. (2001), "The Role of Justice in Organizations: A Meta-Analysis", *Organizational Behavior and Human Decision Processes*, Vol. 86 No. 2, pp. 278–321.

Cohen-Charash, Y. and Spector, P.E. (2001), "The role of justice in organizations: A meta-analysis", *Organizational Behavior and Human Decision Processes*, Vol. 86 No. 2, pp. 278–321.

Colquitt, J.A. (2001), "On the dimesionality of organizational justice: a construct validation of a measure", *Journal of Applied Psychology*, Vol. 86 No. 3, pp. 386–400.

Colquitt, J.A., Greenberg, J. and Zapata-Phelan, C.P. (2005), "What is organizational justice? A historical overview", *Handbook of Organizational Justice*, Vol. 1, pp. 3–58.

Conley, C. and Tosti-Kharas, J. (2014), "Crowdsourcing content analysis for managerial research", *Management Decision*, Vol. 52 No. 4, pp. 675–688.

Cropanzano, R., Goldman, B. and Folger, R. (2003), "Deontic justice: The role of moral principles in workplace fairness", *Journal of Organizational Behavior*, Vol. 24 No. 8, pp. 1019–1024.

Cropanzano, R.S., Ambrose, M.L., Colquitt, J.A. and Rodell, J.B. (2015), "Measuring Justice and Fairness", *The Oxford Handbook of Justice in the Workplace*, pp. 187–202.

Deng, X.N., Joshi, K.D. and Galliers, R.D. (2016), "The Duality Of Empowerment And Marginalization In Microtask Crowdsourcing: Giving Voice To The Less Powerful Through Value Sensitive Design", *MIS Quarterly*, Vol. 40 No. 2, pp. 279–302.

Deutsch, M. (1975), "Equity, Equality, and Need: What Determines Which Value Will Be Used as the Basis of Distributive Justice?", *Journal of Social Issues*, Vol. 31 No. 3, pp. 137–149.

Divakaran, P.K.P. (2017), "Technological Forecasting & Social Change The netnographic method as early warning : Linking antecedents of pre- release behavior of technology-enabled community to future market trends", *Technological Forecasting & Social Change*, Elsevier, Vol. 125, pp. 245–257.

Echambadi, R., Campbell, B. and Agarwal, R. (2006), "Encouraging best practice in quantitative management research: An incomplete list of opportunities", *Journal of Management Studies*, Vol. 43 No. 8, pp. 1801–1820.

Erat, S. and Krishnan, V. (2012), “Managing Delegated Search Over Design Spaces”, *Management Science*, Vol. 58 No. 3, pp. 606–623.

Faullant, R. and Dolfus, G. (2017), “Everything community? Destructive processes in communities of crowdsourcing competitions”, *Business Process Management Journal*, Vol. 23 No. 6, pp. 1108–1128.

Faullant, R., Fueller, J. and Hutter, K. (2017), “Fair play: Perceived fairness in crowdsourcing competitions and the customer relationship-related consequences”, *Management Decision*, Vol. 55 No. 9, pp. 1924–1941.

Fedorenko, I., Berthon, P. and Rabinovich, T. (2017), “Crowded identity: Managing crowdsourcing initiatives to maximize value for participants through identity creation”, *Business Horizons*, Vol. 60 No. 2, pp. 155–165.

Fehr, E. and Schimidt, K.M. (1999), “A Theory of Fairness , Competition , and Cooperation, *The Quarterly Journal of Economics*, Vol. 114 No. 3, pp. 817–868.

Feller, J., Finnegan, P., Hayes, J. and O’Reilly, P. (2012), “‘Orchestrating’ sustainable crowdsourcing: A characterisation of solver brokerages”, *Journal of Strategic Information Systems*, Elsevier B.V., Vol. 21 No. 3, pp. 216–232.

Fieseler, C., Bucher, E., Pieter, C. and Hoffmann, C.P. (2019), “Unfairness by Design ? The Perceived Fairness of Digital Labor on Crowdworking Platforms”, *Journal of Business Ethics*, Springer Netherlands, Vol. 156 No. 4, pp. 987–1005.

Foege, J.N., Dragsdahl, G., Tietze, F. and Oliver, T. (2019), “Reconceptualizing the paradox of openness : How solvers navigate sharing- protecting tensions in crowdsourcing”, *Research Policy*, Elsevier, Vol. 48 No. 6, pp. 1323–1339.

Franke, N., Keinz, P. and Klausberger, K. (2013), “Does this sound like a fair deal?: Antecedents and consequences of fairness expectations in the individual’s decision to participate in firm innovation”, *Organization Science*, Vol. 24 No. 5, pp. 1495–1516.

Di Gangi, P.M., Wasko, M.M. and Hooker, R.E. (2010), “Getting customers’ ideas to work for you: Learning from Dell how to succeed with online user innovation communities”, *MIS Quarterly Executive*, Vol. 9 No. 4, pp. 213–228.

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

Gefen, D., Gefen, G. and Carmel, E. (2016), “How project description length and expected duration affect bidding and project success in crowdsourcing software development”, *Journal of Systems and Software*, Vol. 116, pp. 75–84.

Gilliland, S.W. (1993), “The Perceived Fairness of Selection Systems: An Organizational Justice Perspective”, *Source: The Academy of Management Review*, Vol. 18 No. 4, pp. 694–734.

Greenberg, J. (1987), “A Taxonomy of Organizational Justice Theories.”, *Academy of Management Review*, Vol. 12 No. 1, pp. 9–22.

Greenberg, J. (1990), “Organizational Justice: Yesterday, Today, and Tomorrow”, *Journal of Management*, Vol. 16 No. 2, pp. 399–432.

Greenberg, J. and Scott, K.S. (1996), “Why do workers bite the hands that feed them? Employee theft as a social exchange process”, *Research in Organizational Behavior*, Vol. 18, pp. 111–156.

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

Hamilton, B.H. and Nickerson, J.A. (2003), “Correcting for Endogeneity in Strategic Management Research”, *Strategic Organization*, Vol. 1, pp. 51–78.

Hannah, D.R. and Robertson, K. (2015), “Why and how do employees break and bend confidential information protection rules?”, *Journal of Management Studies*, Vol. 52 No. 3, pp. 381–413.

Hausman, J., Hall, B.H. and Griliches, Z. (1984), “Econometric Models for Count Data with an Application to the Patents-R & D Relationship”, *Econometrica*, Vol. 52 No. 4, pp. 909–938.

Howe, J. (2006), “The Rise of Crowdsourcing”, *Wired Magazine*, Vol. 14 No. 6, pp. 1–4.

Howells, J. (2006). “Intermediation and the role of intermediaries in innovation”, *Research policy*, Vol. 35 No. 5, pp. 715-728.

Jeppesen, L.B. and Lakhani, K.R. (2010), “Marginality and Problem-Solving Effectiveness in Broadcast Search”, *Organization Science*, Vol. 21 No. 5, pp. 1016–1033.

Jian, L., Yang, S., Ba, S., Lu, L. and Jiang, L.C. (2019), “Managing The Crowds: The Effect Of Prize Guarantees And In-Process Feedback On Participation In Crowdsourcing Contests”, *MIS Quarterly*, Vol. 43 No. 1, pp. 97–112.

Jokela, P. and Söderman, A. (2017), “Re-examining the link between fairness and commitment in buyer-supplier relationships”, *Journal of Purchasing and Supply Management*, Vol. 23 No. 4, pp. 268–279.

Kim, W.C. and Mauborgne, R.A. (1993), “Procedural Justice, Attitudes, and Subsidiary Top Management Compliance with Multinationals’ Corporate Strategic Decisions”, *Academy of Management Journal*, Vol. 36 No. 3, pp. 502–526.

Kohler, T. and Nickel, M. (2017), “Crowdsourcing business models that last”, *Journal of Business Strategy*, Vol. 38 No. 2.

Konovsky, M.A. and Cropanzano, R. (1991), “Perceived Fairness of Employee Drug Testing as a Predictor of Employee Attitudes and Job Performance”, *Journal of Applied Psychology*, Vol. 76 No. 5, p. 698.

Korsgaard, M.A., Schweiger, D.M. and Sapienza, H.J. (1995), “Building Commitment , Attachment , and Trust in Strategic Decision-Making Teams : The Role of Procedural Justice”, *Academy of Management Journal*, Vol. 38 No. 1, pp. 60–84.

Kozinets, R. V. (2002), “The Field Behind the Screen: Using Netnography for Marketing Research in Online Communities”, *Journal of Marketing Research*, Vol. 39 No. 1, pp. 61–72.

Kozinets, R. V. (2010), *Netnography: Doing Ethnographic Research Online*, SAGE Publications.

Leventhal, G.S. (1980), “What should be done with equity theory? New approaches to the study of fairness in social relationships”, *Social Exchange: Advances in Theory and*

Research, pp. 27–55.

Li, D. and Hu, L. (2017), “Exploring the effects of reward and competition intensity on participation in crowdsourcing contests”, *Electronic Markets*, Electronic Markets, Vol. 27 No. 3, pp. 199–210.

Li, H., Bingham, J.B., Umphress, E.E., Li, H., Bingham, J.B. and Umphress, E.E. (2007), “New Product Development Organization Science infiunH Fairness from the Top : Perceived Procedural Justice and Collaborative Problem Solving in New Product Development”, *Organization Science*, Vol. 18 No. 2, pp. 200–216.

Liang, H., Wang, M.M., Wang, J.J. and Xue, Y. (2018), “How intrinsic motivation and extrinsic incentives affect task effort in crowdsourcing contests: A mediated moderation model”, *Computers in Human Behavior*, Elsevier Ltd, Vol. 81, pp. 168–176.

Lüttgens, D., Pollok, P., Antons, D. and Piller, F. (2014), “Wisdom of the crowd and capabilities of a few: internal success factors of crowdsourcing for innovation”, *Journal of Business Economics*, Vol. 84 No. 3, pp. 339–374.

Masterson, S.S., Lewis, K., Goldman, B.M. and Taylor, M.S. (2000), “Integrating Justice and Social Exchange: The Differing Effects of Fair Procedures and Treatment on Work Relationships”, *Academy of Management Journal*, Vol. 43 No. 3, pp. 733–748.

Mazzola, E., Acur, N., Piazza, M. and Perrone, G. (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*, Vol. 35 No. 6, pp. 908–929.

Nambisan, S. and Baron, R.A. (2010), “Different Roles, Different Strokes: Organizing Virtual Customer Environments to Promote Two Types of Customer Contributions”, *Source: Organization Science*, Vol. 21 No. 2, pp. 554–572.

Natalicchio, A., Messeni Petruzzelli, A. and Garavelli, A.C. (2017), “Innovation problems and search for solutions in crowdsourcing platforms – A simulation approach”, *Technovation*, Elsevier Ltd, Vol. 64–65 No. November 2015, pp. 28–42.

Parsloe, S.M. (2015), “Discourses of Disability , Narratives of Community : Reclaiming an Autistic Identity Online Discourses of Disability , Narratives of Community : Reclaiming an Autistic Identity Online”, *Journal of Applied Communication Research*, Vol. 43 No. 3, pp. 336–356.

Paulus, P. B. and Yang, H. C. (2000), “Idea generation in groups: A basis for creativity in organizations”, *Organizational behavior and human decision processes*, Vol. 82 No. 1, pp. 76-87.

Plourde, Y., Parker, S.C. and Schaan, J.L. (2014), “Expatriation and its effect on headquarters’ attention in the multinational enterprise”, *Strategic Management Journal*, Vol. 35, pp. 938–947.

Pollok, P., Lüttgens, D. and Piller, F.T. (2019), “Attracting solutions in crowdsourcing contests: The role of knowledge distance, identity disclosure, and seeker status”, *Research Policy*, Elsevier, Vol. 48 No. 1, pp. 98–114.

Rupp, D.E., Shapiro, D.L., Folger, R., Skarlicki, D.P. and Shao, R. (2017), “‘A Critical Analysis of the Conceptualization and Measurement of “Organizational Justice”: Is it Time for Reassessment?’”, *Academy of Management Annals*, Vol. 11 No. 2, pp. 919–

959.

Salter, A., Ter Wal, A.L.J., Criscuolo, P. and Alexy, O. (2015), "Open for ideation: Individual-level openness and idea generation in R&D", *Journal of Product Innovation Management*, Vol. 32 No. 4, pp. 488–504.

Schemmann, B., Herrmann, A.M., Chappin, M.M.H. and Heimeriks, G.J. (2016), "Crowdsourcing ideas: Involving ordinary users in the ideation phase of new product development", *Research Policy*, Vol. 45 No. 6, pp. 1145–1154.

Schlagwein, D., Cecez-Kecmanovic, D. and Hanckel, B. (2019), "Ethical norms and issues in crowdsourcing practices: A Habermasian analysis", *Information Systems Journal*, Vol. 29 No. 4, pp. 811–837.

Shao, B., Shi, L., Xu, B. and Liu, L. (2012), "Factors affecting participation of solvers in crowdsourcing: An empirical study from China", *Electronic Markets*, Vol. 22 No. 2, pp. 73–82.

Sheppard, B.H. and Lewicki, R.J. (1987), "Toward General Principles of Managerial Fairness", *Social Justice Research*, Vol. 1 No. 2, pp. 161–176.

Sieg, J.H., Wallin, M.W. and von Krogh, G. (2010), "Managerial challenges in open innovation: A study of innovation intermediation in the chemical industry", *R and D Management*, Vol. 40 No. 3, pp. 281–291.

Simmers, C.A. and McMurray, A.J. (2018), "Organisational Justice And Managing Workplace Innovation : How Important Are Formal Procedures ? Literature Review and Research Model", *International Journal of Innovation Management*, pp. 1950026-1-1950026–21.

Simonton, D.K. (2003), "Scientific Creativity as Constrained Stochastic Behavior: The Integration of Product, Person, and Process Perspectives", *Psychological Bulletin*, Vol. 129 No. 4, pp. 475–494.

Steils, N. and Hanine, S. (2019), "Recruiting valuable participants in online IDEA generation : The role of brief instructions", *Journal of Business Research*, Elsevier, Vol. 96, pp. 14–25.

Stevens, J. (1996), *Applied Multivariate Statistics for the Social Sciences (3rd Edition), Mahwah, NJ: Lawrence Erlbaum*.

Strauss, A. and Corbin, J. (1990), "Basics of Qualitative Research", *Basics of Qualitatice Research*, SAGE Publications.

Sun, Y., Wang, N., Yin, C. and Zhang, J.X. (2015), "Understanding the relationships between motivators and effort in crowdsourcing marketplaces: A nonlinear analysis", *International Journal of Information Management*, Vol. 35 No. 3, pp. 267–276.

Terwiesch, C. and Xu, Y. (2008), "Innovation Contests, Open Innovation, and Multiagent Problem Solving", *Management Science*, Vol. 54 No. 9, pp. 1529–1543.

van den Bos, K., Vermunt, R. and Wil. (1997), "Procedural and distributive justice: what is fair depends more on what comes first than on what comes next", *Journal of Personality and Social Psychology*, Vol. 72 No. 1, pp. 95–104.

Weber, M. (1985), "Method Of Multiattribute Decision Making With Incomplete

Information", *Management Science*, Vol. 31 No. 11, pp. 1365–1371.

Witman, P. (2005), "The Art and Science of Non-Disclosure Agreements", *Communications of the Association for Information Systems*, Vol. 16, pp. 260–269.

Wooldridge, J.M. (2002), *Econometric Analysis of Cross Section and Panel Data*, *MIT Press*.

Wooten, J.O. and Ulrich, K.T. (2017), "Idea Generation and the Role of Feedback: Evidence from Field Experiments with Innovation Tournaments", *Production and Operations Management*, Vol. 26 No. 1, pp. 80–99.

Ye, H. (Jonathan) and Kankanhalli, A. (2017), "Solvers' participation in crowdsourcing platforms: Examining the impacts of trust, and benefit and cost factors", *Journal of Strategic Information Systems*, Vol. 26 No. 2, pp. 101–117.

Yousaf, S. and Xiucheng, F. (2018), "Humanizing stigmatized places : Inter-group contact and attitude change toward Pakistan and Iran in the ' Humans of New York ' Facebook space", *Journal of Business Research*.

Zheng, H., Li, D. and Hou, W. (2011), "Task Design, Motivation, and Participation in Crowdsourcing Contests", *International Journal of Electronic Commerce*, Vol. 15 No. 4, pp. 57–88.

Zogaj, S., Bretschneider, U. and Leimeister, J.M. (2014), "Managing crowdsourced software testing: a case study based insight on the challenges of a crowdsourcing intermediary", *Journal of Business Economics*, Vol. 84 No. 3, pp. 375–405.

Zou, L., Zhang, J. and Liu, W. (2015), "Perceived justice and creativity in crowdsourcing communities: Empirical evidence from China", *Social Science Information*, Vol. 54 No. 3, pp. 253–279.

TABLES

Keyword	Relevant discussions
fair	26
justice	4
equit*	3
honest	4
right*	4
correct*	1
wrong*	7
integrity	1
ethic*	2
transparen*	2
Total	54

Table 1. Discussion selection through keywords

Examples of discussions*	Fairness code	Fairness factor
"I see more and more 3D designers joining 99designs, but also, more and more of them are quitting. Main reason is we, 3D designers **are underpaid for our job**, **and prizes on contests here are far too low than they should be**. At first chance to earn some serious money, every designer will leave this forever. […] I tried several freelancing communities and to be honest, only 99designs suits me fine, but that's not good reason to stay here when I can't **earn some decent money and be payed fairly** for job I'm doing". [Increase prize for 3D contests]	Underpayment feelings	Prize award
"This is the reason I do not participate in illustration projects here, or very rarely. And illustrator charges differently. He has a base price for an illustration, based on the amount of time it takes him to create it. And then on top of that, he puts usage rights. Exclusive or non-exclusive, locally or globally, which media, for how long… that is where the money is. If a book I illustrate gets translated - I get more money. If that character gets picked up for a tv show - I get money. If they then produce merchandising - I get money. I own the character, too… they cannot hire someone else to make drawings or a spin off from my character. If I create a children's book character on 99D… that is it. **The seeker buys the rights, it becomes a huge hit - nothing**. **I am stuck with $130 or whatever for the initial drawing**…" [What if scarlett johannsenn is member of 99d and oneday…. (question about stock)]	Intellectual Property Right	
"Yep hence I will not touch illustration contests on 99D. It's insulting to some of the amazing talent out there. It's **hours and hours of work**, it's a very **unique skill** and the hours that go into that level of skill **should be paid in kind**". [I feel like the art and illustration prizes are too low]	Solvers' effort and skills	
"And yes, any reason is better than no reason at all. I understand that there might be lot of things behind this [referring to **refunds**, i.e. seeker asking to **receive back her/his money without selecting a winning solution** claiming she/he has not found a suitable design]…but **what if the CH** [Contest	Seekers' refund	Award guaranteed

Holder, i.e. Seeker] **just wanted some ideas**…**I don't think this is fair**, and I know that many designers (if not all of them) think the same". [We deserve an explanation! (regarding refunds)]		
"[…] The best way to **avoid losing out on non-guaranteed** contest is to assess the client. Visit their profile, see how active they are, check if they have refunds, dissect their brief. **If you get the idea that they are invested in their contest and spending time to really engage with designers** – that is the safest kind of non-guaranteed contest you could find! ☺" [Contests that aren't guaranteed]	Seekers' commitment	
"I think **blind contests are disrespectful of designers**. The client is allowed to choose the design/designer, but the designer doesn't get to know the taste level of who they are working with. […] **I like to see what they are giving four or five stars to**, so I can see if I even want to participate in their contest. Sometimes they give five stars to designs that I think are awful, so that would allow me to pass over that contest and find one I'd rather enter. **I don't think it's fair** to designers to make us work for a CH who may have horrible taste". [Make ALL Contests Blind!]	Accessing ratings assigned by seekers	Non-blind
"I feel it too [feeling of unfairness when competing with solvers submitting poor quality designs], in one of my contests. I can not show it, because it's a **private contest**. My entries and something frightening from entry level designer have 5 stars and **I cannot understand why my work is near on a level with a bad quality design**. It's good, that my mood is changing fast and I'm setting myself up for a positive…with beer…in my saturday morning ☺". [Poor design quality]	Comparing the quality of the solution proposals	
"**I do not feel everything goes right and fair in a blind contest**. There is definitively pros-and-cons in **blind and non-blind** contests. One negative aspect in blind contests is the **inability to spot a designer infringing rights** until designs are revealed". [No more nightmare for non-blind contest]	Infringements reporting	
*In bold we highlighted the words more relevant for the open coding procedure. In parentheses we reported the name of the conversation.		

Table 2. Results from netnographic analysis

Seekers' decision	Relevant discussions	
Prize award	13	24.1%
Award Guaranteed	19	35.2%
Non-blind	22	40.7%
Total	54	100%

Table 3. Distribution of discussions by seekers' decisions

Variables	Mean	SD	Max	Min
Self-selected solvers	38.7	51.61	1078	1
Submitted ideas	147.1	181.38	3510	2
Multiple submission	4.06	1.90	17.43	1
Seeker type				
Firm	0.54	0.50	1	0
Private	0.05	0.22	1	0
No profit	0.19	0.40	1	0
Unknown	0.21	0.41	1	0
Contest type				
Logo	0.64	0.48	1	0
Website&APP	0.11	0.31	1	0
Packaging&ADV	0.13	0.33	1	0
Art,Book&Merchandising	0.12	0.33	1	0
Duration	5.44	6.35		
Seeker identity	0.77	0.42	1	0
Competition	2.17	1.69	5	0
Month				
January	0.10	0.30	1	0
February	0.10	0.29	1	0
March	0.10	0.30	1	0
April	0.10	0.30	1	0
May	0.12	0.33	1	0
June	0.11	0.31	1	0
July	0.10	0.30	1	0
August	0.10	0.28	1	0
September	0.10	0.31	1	0
October	0.08	0.28	1	0
Prize award	325,1	278.4	3500	20
Award guaranteed	0.82	0.38	1	0
Non-blind	0.68	0.46	1	0

Table 4. Descriptive statistics

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
(1)Self-selected solvers	1																										
(2)Submitted ideas	0.94*	1																									
(3) Multiple submission	0.63*	0.22	1																								
(4)Firm	0.06	0.09*	0.13	1																							
(5)Private	-0.002	0.01	0.03*	-0.25*	1																						
(6)No profit	-0.02	-0.01	0.06	-0.54*	-0.11*	1																					
(7)Unknown	-0.05	-0.11*	-0.23	-0.56*	-0.12*	-0.25*	1																				
(8)Logo	0.31*	0.32*	-0.01	0.08*	-0.07*	0.08*	-0.14*	1																			
(9)Website&APP	-0.16*	-0.16*	0.08*	-0.03	-0.02	0.08*	-0.04	-0.46*	1																		
(10)Packaging&ADV	-0.19*	-0.20*	-0.02	0.12*	-0.05	-0.12*	-0.01	-0.51*	-0.13*	1																	
(11)Art,Book&Merchandising	-0.11*	-0.11*	-0.03	-0.21*	0.18*	-0.08*	0.24*	-0.51*	-0.13*	-0.14*	1																
(12)Duration	0.13*	0.11*	-0.02	-0.03	-0.02	0.01	0.04	-0.03	0.10*	-0.02	-0.03	1															
(13)Seeker identity	0.04	0.10	0.11	0.23	0.52	0.08	0.24	0.92	0.11	0.04	0.03	0.23	1														
(14)Competitiom	-0.01*	0.02	0.08	0.13	-0.01	0.02	-0.18*	0.01	0.14	-0.03	-0.11*	0.03	-0.11*	1													
(15)January	-0.08*	-0.08*	-0.03	-0.04	0.03	0.005	0.03	-0.24*	0.05	0.07*	0.22*	-0.03	0.03	-0.01	1												
(16)February	0.05	0.07*	0.03	0.02	0.02	-0.08*	0.04	0.03	-0.004	0.005	-0.04	0.08*	0.02	-0.03	-0.11*	1											
(17)March	0.02	0.01	0.02	0.004	0.008	-0.003	-0.01	0.03	-0.04	0.01	-0.01	0.04	0.06	-0.03*	-0.11*	-0.11*	1										
(18)April	-0.01	0.01	0.08	0.02	0.03	0.03	-0.07*	0.07*	-0.02	-0.03	-0.05	-0.02	0.01	-0.04	-0.11*	-0.11*	-0.11*	1									
(19)May	-0.01	-0.02	-0.07*	-0.01	-0.05	0.008	0.03	0.002	0.02	0.01	-0.03	-0.05	0-06	0.03	-0.12*	-0.12*	-0.13*	-0.12*	1								
(20)June	0.14*	0.13*	-0.01	-0.02	0.005	-0.02	0.04	0.07*	-0.05	-0.004	-0.06	0.05	0.04	-0.01*	-0.11*	-0.11*	-0.12*	-0.11*	-0.13*	1							
(21)July	-0.02	-0.01	0.02	0.06	-0.02	-0.001	-0.06	0.03	-0.05	0.03	-0.02	-0.05	0.04	-0.01	-0.11*	-0.10*	-0.11*	-0.11*	-0.12*	-0.11*	1						
(22)August	-0.05	-0.07*	0.01	-0.02	0.03	0.02	-0.01	0.03	0.01	-0.05	0.0004	-0.02	0.04	0.01	-0.11*	-0.11*	-0.11*	-0.11*	-0.12*	-0.11*	-0.11*	1					
(23)September	-0.03	-0.04	-0.03	-0.03	-0.02	0.03	0.01	-0.002	0.05	-0.02	-0.03	-0.02	0.03	0.03*	-0.11*	-0.11*	-0.12*	-0.11*	-0.13*	-0.12*	-0.11*	-0.11*	1				
(24)October	-0.001	0.002	0.01*	0.02	-0.02	-0.002	-0.01	-0.02	0.03	-0.02	0.02	0.01	0.002	0.05	-0.10*	-0.10*	-0.10*	-0.10*	-0.11*	-0.10*	-0.10*	-0.10*	-0.10*	1			
(25)Award	0.13*	0.15*	0.20	0.03	-0.04	0.05	-0.07*	-0.14*	0.50*	-0.10*	-0.16*	0.12*	0.07	0.14	-0.02	-0.02	0.02	0.002	0.05	-0.01	-0.02	-0.05	-0.01	0.05	1		
(26)Award guaranteed	0.03	0.10*	0.29*	0.28*	0.08*	0.17*	-0.55*	-0.02	0.02	-0.03	0.03	-0.01	0.52	0.16*	0.004	-0.06	-0.02	0.02	-0.01	-0.06*	0.02	0.04	0.04	0.01	0.02	1	
(27)Non-blind	0.15*	0.13*	-0.01*	0.007	-0.01	-0.01	0.01	0.39*	-0.50*	-0.06	-0.04	-0.12*	0.01	0.22*	-0.06	0.04	0.02	0.03	-0.02	0.03	0.03	-0.03	-0.02	-0.02	-0.29*	-0.09*	1

* $p < 0.05$

Table 5. Correlation matrix

	Self-selected solvers				
	Model 1	Model 2	Model 3	Model 4	Model 5
Seeker identity	0.0667	0.0648	0.0631	0.0608	0.0415
	(0.126)	(0.118)	(0.126)	(0.126)	(0.118)
Firm	0.0827	0.0131	0.0213	0.0880	-0.0672
	(0.132)	(0.125)	(0.136)	(0.132)	(0.128)
Private	0.140	0.112	0.0792	0.144	0.0318
	(0.155)	(0.145)	(0.158)	(0.155)	(0.147)
No profit	-0.0436	-0.0759	-0.105	-0.0374	-0.157
	(0.138)	(0.130)	(0.142)	(0.138)	(0.133)
Logo	0.698***	0.500***	0.729***	0.686***	0.528***
	(0.0699)	(0.0671)	(0.0713)	(0.0702)	(0.0682)
Website &APP	-0.641***	-1.140***	-0.610***	-0.588***	-1.022***
	(0.0917)	(0.0940)	(0.0926)	(0.0970)	(0.0982)
Packaging & ADV	-0.608***	-0.665***	-0.581***	-0.599***	-0.607***
	(0.0867)	(0.0817)	(0.0875)	(0.0868)	(0.0824)
Duration	0.401***	0.267***	0.383***	0.409***	0.252***
	(0.0526)	(0.0486)	(0.0527)	(0.0528)	(0.0482)
Competition	-0.0238*	-0.0322**	-0.0263*	-0.0202	-0.0301**
	(0.0121)	(0.0114)	(0.0121)	(0.0123)	(0.0115)
January	-0.106	-0.0921	-0.105	-0.101	-0.0816
	(0.0973)	(0.0908)	(0.0972)	(0.0972)	(0.0903)
February	0.0796	0.113	0.0865	0.0794	0.124
	(0.0964)	(0.0900)	(0.0963)	(0.0963)	(0.0894)
March	-0.0750	-0.0476	-0.0724	-0.0748	-0.0425
	(0.0946)	(0.0880)	(0.0945)	(0.0945)	(0.0873)
April	-0.151	-0.135	-0.151	-0.148	-0.130
	(0.0950)	(0.0886)	(0.0949)	(0.0950)	(0.0879)
May	-0.0446	-0.0506	-0.0445	-0.0423	-0.0490
	(0.0905)	(0.0844)	(0.0904)	(0.0904)	(0.0837)
June	0.185*	0.162^{+}	0.188*	0.184*	0.166^{+}
	(0.0938)	(0.0872)	(0.0936)	(0.0937)	(0.0865)
July	-0.102	-0.0752	-0.100	-0.0991	-0.0703
	(0.0954)	(0.0892)	(0.0952)	(0.0953)	(0.0885)
August	-0.287**	-0.198*	-0.292**	-0.279**	-0.191*
	(0.0958)	(0.0895)	(0.0956)	(0.0958)	(0.0890)
September	-0.144	-0.0688	-0.152	-0.140	-0.0718
	(0.0941)	(0.0879)	(0.0940)	(0.0940)	(0.0873)
Prize Award		0.508***			0.524***
		(0.0400)			(0.0399)
Award guaranteed			0.131*		0.203***
			(0.0630)		(0.0587)
Non-blind				0.0850*	0.131**
				(0.0520)	(0.0483)
Constant	2.521***	0.108	2.474***	2.440***	-0.178
	(0.132)	(0.226)	(0.133)	(0.141)	(0.235)
N	1067	1067	1067	1067	1067
Log-likelihood	-4634.20	-4555.36	-4632.07	-4632.88	-4546.52
Chi-square test	0.0000	0.0000	0.0000	0.0000	0.0000
Log-likelihood ratio test	-	5.06***	1.45*	0.97*	5.17***

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

Table 6. Negative binomial regression results

	Submitted ideas				
	Model 1	Model 2	Model 3	Model 4	Model 5
Client identity	0.0825	0.0994	0.0713	0.0784	0.0716
	(0.128)	(0.122)	(0.128)	(0.128)	(0.121)
Firm	0.276^{*}	0.193	0.106	0.280^{*}	0.00855
	(0.135)	(0.129)	(0.139)	(0.135)	(0.131)
Private	0.345^{*}	0.300^{*}	0.178	0.349^{*}	0.117
	(0.161)	(0.152)	(0.164)	(0.161)	(0.154)
No profit	0.152	0.104	-0.0183	0.155	-0.0895
	(0.142)	(0.135)	(0.145)	(0.142)	(0.137)
Logo	0.589^{***}	0.396^{***}	0.687^{***}	0.583^{***}	0.500^{***}
	(0.0736)	(0.0712)	(0.0744)	(0.0740)	(0.0714)
Website & APP	-0.569^{***}	-1.057^{***}	-0.484^{***}	-0.541^{***}	-0.915^{***}
	(0.0952)	(0.0968)	(0.0948)	(0.101)	(0.1000)
Packaging & ADV	-0.674^{***}	-0.747^{***}	-0.589^{***}	-0.669^{***}	-0.628^{***}
	(0.0900)	(0.0855)	(0.0899)	(0.0902)	(0.0850)
Duration	0.352^{***}	0.213^{***}	0.307^{***}	0.356^{***}	0.171^{***}
	(0.0570)	(0.0528)	(0.0551)	(0.0573)	(0.0505)
Competition	-0.00176	-0.0154	-0.00875	-0.0000139	-0.0197
	(0.0129)	(0.0123)	(0.0127)	(0.0130)	(0.0122)
January	-0.135	-0.0970	-0.131	-0.132	-0.0822
	(0.101)	(0.0955)	(0.100)	(0.102)	(0.0938)
February	0.116	0.182^{+}	0.132	0.116	0.200^{*}
	(0.102)	(0.0965)	(0.101)	(0.102)	(0.0945)
March	-0.0987	-0.0525	-0.0934	-0.0963	-0.0417
	(0.100)	(0.0941)	(0.0990)	(0.100)	(0.0921)
April	-0.136	-0.101	-0.132	-0.134	-0.0904
	(0.101)	(0.0948)	(0.0996)	(0.101)	(0.0927)
May	-0.108	-0.0712	-0.110	-0.105	-0.0752
	(0.0959)	(0.0902)	(0.0946)	(0.0959)	(0.0883)
June	0.150	0.155^{+}	0.166^{+}	0.151	0.175^{+}
	(0.100)	(0.0939)	(0.0988)	(0.100)	(0.0918)
July	-0.108	-0.0545	-0.0974	-0.106	-0.0392
	(0.101)	(0.0951)	(0.0997)	(0.101)	(0.0931)
August	-0.387^{***}	-0.269^{**}	-0.392^{***}	-0.382^{***}	-0.260^{**}
	(0.101)	(0.0953)	(0.0997)	(0.101)	(0.0934)
September	-0.228^{*}	-0.126	-0.243^{*}	-0.224^{*}	-0.135
	(0.0992)	(0.0935)	(0.0980)	(0.0993)	(0.0917)
Prize Award		0.497^{***}			0.521^{***}
		(0.0412)			(0.0406)
Award guaranteed			0.379^{***}		0.445^{***}
			(0.0655)		(0.0611)
Non-blind				0.0437^{+}	0.0881^{*}
				(0.0545)	(0.0504)
Constant	3.844^{***}	1.479^{***}	3.676^{***}	3.802^{***}	1.054^{***}
	(0.139)	(0.235)	(0.138)	(0.149)	(0.242)
N	1067	1067	1067	1067	1067
Log-likelihood	-6103.99	-6032.46	-6088.67	-6101.67	-6006.91
Chi-square test	0.0000	0.0000	0.0000	0.0000	0.0000
Log-likelihood ratio test	-	4.96^{***}	3.45^{***}	0.64^{*}	5.27^{***}

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

Table 7. Negative binomial regression results with an alternative dependent variable

	Multiple Submissions				
	Model 1	Model 2	Model 3	Model 4	Model 5
Client identity	0.0413	-0.00498	-0.0308	0.0126	-0.136
	(0.350)	(0.345)	(0.343)	(0.350)	(0.336)
Firm	1.008**	1.005**	0.396	1.035**	0.372
	(0.368)	(0.363)	(0.371)	(0.368)	(0.363)
Private	0.920*	0.945*	0.332	0.948*	0.343
	(0.427)	(0.421)	(0.426)	(0.426)	(0.417)
No profit	0.994**	1.035**	0.345	1.019**	0.364
	(0.384)	(0.378)	(0.387)	(0.384)	(0.379)
Logo	-0.265	-0.478*	0.0145	-0.319+	-0.286
	(0.191)	(0.192)	(0.191)	(0.193)	(0.192)
Website & APP	0.177	-0.480+	0.465+	0.323	-0.0329
	(0.250)	(0.273)	(0.249)	(0.263)	(0.276)
Packaging & ADV	-0.302	-0.365	-0.0267	-0.299	-0.0672
	(0.235)	(0.232)	(0.233)	(0.235)	(0.228)
Duration	0.119	-0.0116	0.0103	0.153	-0.0981
	(0.147)	(0.147)	(0.145)	(0.148)	(0.144)
Competition	0.0459	0.0289	0.0268	0.0581+	0.0244
	(0.0345)	(0.0341)	(0.0338)	(0.0351)	(0.0338)
January	-0.0631	-0.0154	-0.0429	-0.0621	0.0154
	(0.271)	(0.267)	(0.265)	(0.271)	(0.260)
February	0.384	0.429	0.417	0.371	0.454+
	(0.272)	(0.269)	(0.267)	(0.272)	(0.261)
March	0.245	0.254	0.276	0.247	0.292
	(0.265)	(0.261)	(0.259)	(0.265)	(0.254)
April	0.541*	0.568*	0.524*	0.544*	0.560*
	(0.268)	(0.264)	(0.262)	(0.268)	(0.256)
May	-0.190	-0.168	-0.209	-0.183	-0.176
	(0.254)	(0.251)	(0.249)	(0.254)	(0.243)
June	0.194	0.221	0.236	0.196	0.275
	(0.264)	(0.260)	(0.258)	(0.263)	(0.252)
July	0.186	0.220	0.192	0.186	0.233
	(0.269)	(0.265)	(0.263)	(0.268)	(0.257)
August	0.143	0.245	0.0988	0.159	0.236
	(0.268)	(0.264)	(0.262)	(0.268)	(0.257)
September	-0.0440	0.0377	-0.115	-0.0439	-0.0280
	(0.264)	(0.260)	(0.258)	(0.263)	(0.253)
Prize Award		0.676***			0.777***
		(0.120)			(0.118)
Award guaranteed			1.243***		1.370***
			(0.180)		(0.177)
Non-blind				0.267*	0.414**
				(0.147)	(0.141)
_cons	2.993***	-0.329	2.503***	2.744***	-1.747*
	(0.369)	(0.694)	(0.368)	(0.393)	(0.709)
N	1067	1067	1067	1067	1067
R^2	0.072	0.099	0.112	0.075	0.152
adj. R^2	0.056	0.083	0.096	0.058	0.135
F	4.504	6.052	6.966	4.452	8.927

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

Table 8. OLS regression results considering multiple submissions

FOOTNOTES

1. The '*' has been used to include any possible part of a keyword that is omitted, e.g., the keyword '*fair*' includes in the search, also, all the following keywords: unfair, fairness, unfairness, fairly and unfairly.