Crowdsourcing for innovation

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published in
Research Policy
2019

DOI (link to publisher)
10.1016/j.respol.2019.04.005

Research Policy 48 (2019) 1758–1770

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Crowdsourcing for innovation: How related and unrelated perspectives interact to increase creative performance

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ARTICLE INFO

Keywords:
Open innovation
Digitization
Crowdsourcing
Idea generation
Educational background
Perspective

ABSTRACT

In recent years, several organizations have opened up their innovation processes to individuals from outside of the organization by means of digital crowdsourcing. The literature on crowdsourcing has emphasized the importance of using digital technology to reach far beyond organizational boundaries and include individuals with (educational) backgrounds that are very different and unrelated to those within the organization in its innovation process. It has been argued that such individuals will contribute novel insights because they consider an organization's innovation challenge from different perspectives. Building on the literature on creativity and absorptive capacity, we instead argue that having a *related* perspective will positively affect an individual's idea performance, while *unrelated* perspectives only positively contribute to idea performance in combination with a related perspective. Analyses of 2178 ideas contributed by 948 crowd members to 68 crowdsourced idea challenges show that it is important to consider how (educational) backgrounds can provide individuals with multiple perspectives, which can be either related or unrelated, and study how the interplay of related and unrelated perspectives affects the value of ideas in organizational open innovation initiatives.

1. Introduction

To compete in today's fast-moving business environment, organizations must continuously improve their current offerings by creating new products and services to better meet their customers' changing demands (e.g. Chesbrough, 2003; Laursen and Salter, 2006; West et al., 2014). To fulfill this need for continuous innovation, organizations have been opening up their innovation processes to ideas and suggestions from various parties outside of their organizational boundaries, such as their suppliers, customers, and even competitors (Dahlander and Gann, 2010; Dahlander and Piezunka, 2014; Enkel et al., 2009; West and Bogers, 2014). Recent advances in digitization and digital technologies, especially developments with regard to Web 2.0, have enabled organizations to open up their innovation initiatives even further and reach beyond their immediate network by crowdsourcing innovation-related tasks (e.g. Afuah and Tucci, 2012; Bayus, 2013; Dahlander and Gann, 2010; Howe, 2008).

Crowdsourcing, which is “the act of outsourcing a task to a ‘crowd,’ rather than to a designated agent (an organization, informal or formal team, or individual).. in the form of an open call” (Afuah and Tucci, 2012, p. 355), enables organizations to digitally source their calls for innovative ideas and solutions to online crowds consisting of thousands of individuals who the organization did not previously have access to (e.g. Brabham, 2013; Howe, 2008). However, only a few individuals will actually provide the valuable ideas and suggestions that organizations are seeking as inputs when they open up their innovation processes (e.g. Bayus, 2013; Piezunka and Dahlander, 2015). Recent work on open innovation has emphasized the human aspects of open innovation and specifically how the individuals involved in identifying and absorbing of knowledge from outside of the organization affect organizations' ability to benefit from open innovation (e.g. Ahn et al., 2017; Bogers et al., 2018). Similarly, one would expect that the extent to which individuals from outside the organization are able to *contribute* valuable ideas and suggestions in open innovation initiatives is also likely to depend on their individual characteristics, such as their knowledge backgrounds (e.g. Jeppesen and Lakhani, 2010).

Crowdsourcing theory and practice have been based on the assumption that obtaining ideas from individuals with ‘different’ perspectives from those held by the employees of the organization is a key driver of the success of organizations' crowdsourcing initiatives, because these individuals contribute ideas that are more *novel* for the organization (Jeppesen and Lakhani, 2010; Piezunka and Dahlander, 2015; Poetz and Schreier, 2012). The near limitless reach of the Internet has played a crucial role in enabling these “distant” searches, in which the organization targets large numbers of individuals who, in terms of their backgrounds and perspectives, are very far removed from the

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https://doi.org/10.1016/j.respol.2019.04.005
Received 8 December 2017; Received in revised form 26 March 2019; Accepted 5 April 2019
Available online 07 May 2019
0048-7333/

organization (Afuah and Tucci, 2012). However, for organizations looking for new ideas and innovative solutions through crowdsourcing, these digital affordances also come with an increased risk of "overreaching" – targeting individuals who are too far removed from the organization to contribute ideas that are actually useable–which would substantially lower the efficiency and effectiveness of their crowdsourcing initiatives (e.g. Alexy et al., 2012; Bjelland and Wood, 2008; Dahlander et al., 2016; Katila and Ahuja, 2002; Laursen and Salter, 2006). Thus, in their search for novelty organizations may run the risk of overreaching.

Indeed, the literature on creativity has emphasized that while novelty is important, by itself it is not enough to make an idea valuable for a crowdsourcing organization; ideas also need to be useful and relevant from the perspective of the organization. The research in this field has shown that individuals without a domain-related background find it much more difficult to understand creative problem-solving tasks and come up with *useful and relevant* insights for the organization (e.g. Amabile, 1996; Berg, 2014; Sternberg, 1998; Weisberg, 1998). Moreover, individuals who lack domain-related backgrounds will struggle to express their insights in a way that crowdsourcing organizations will understand (Dahlander and Gann, 2010). If organizations do not understand how ideas will be useful and relevant for them, they are not considered valuable contributions (e.g. Cohen and Levinthal, 1990; Morgan et al., 2018; Piezunka and Dahlander, 2015; Rietzschel et al., 2010; West and Bogers, 2014). Thus, being able to take a related perspective is a necessary element in the process of generating ideas of any value for organizations (Amabile, 1996; Mumford and Gustafson, 1988; Schweisfurth and Raasch, 2018).

In this study, we aim to integrate the literatures on crowdsourcing (that emphasizes the value of unrelated perspectives) with those of creativity and absorptive capacity (that emphasize the value of related perspectives). Specifically, we investigate the role of individuals' related and unrelated perspectives in digital crowdsourced innovation by exploring their educational backgrounds. We posit that one's educational background is a useful, objective, proxy for the perspectives that an individual can bring to bear on an idea generation task. Some educational backgrounds offer multiple perspectives, which may allow individuals to combine a perspective related to the domain of the idea generation task with perspectives that are unrelated. We propose that the possession of an educational background that offers a perspective related to the domain of the digitally crowdsourced idea generation task is valuable in itself, because it contributes to individuals' ability to come up with useful and relevant ideas that enable organizational innovation (Amabile, 1996; Cohen and Levinthal, 1990; Pretz et al., 2003; Sternberg, 1998; Weisberg, 1998; Woodman et al., 1993). Moreover, we argue that an individual's related educational background facilitates the generation of ideas by recombining knowledge from unrelated perspectives to the problem domain, thereby unlocking the potential novelty benefits of an unrelated perspective (e.g. Mumford and Gustafson, 1988). Thus, we argue that combining a related perspective with unrelated perspectives will be more likely to lead to ideas that are useful as well as novel and, therefore, highly valuable for organizational innovation.

This study contributes to our understanding of the drivers of successful open innovation initiatives in several ways. First, our study integrates the literature on crowdsourcing for innovation with the literature on cognitive psychology by considering related and unrelated perspectives as knowledge schemas related to different domains. By describing how individuals engage in creative problem-solving by integrating and recombining pieces of knowledge from within and across domain schemas (e.g. Dane, 2010; Mumford and Gustafson, 1988), this study grounds the different roles that related and unrelated perspectives might play in creativity in the broader cognitive psychology literature on how individuals store and create new knowledge (e.g. Fiske and Taylor, 1991). Unlike previous crowdsourcing studies that have focused on the distance of a contributor's knowledge from the task domain, a knowledge schema perspective allows us to consider the different, but interrelated, roles that related and unrelated perspectives play in the generation of creative ideas. Second, the study highlights the double-edged nature of advances in digitization and digital technologies for organizations engaged in inbound open innovation; organizations' increased ability to perform ever more distant searches increases the risk of organizations "overreaching". Based on our analyses of 2178 contributions to 68 idea generation challenges organized through a digital crowdsourcing platform, we show that individuals whose perspectives are too distant from the domain of the idea generation task (i.e. lacking a perspective related to the domain) contribute ideas of lower value to crowdsourced innovation initiatives. Third, our study contributes to the recent work on open innovation that has emphasized the human aspects of open innovation (e.g. Ahn et al., 2017; Bogers et al., 2018) by considering the individual characteristics of members of the crowd who contribute ideas to organizations' open innovation initiatives. Focusing on the educational backgrounds of individual contributors, our study shows the importance of considering the multiple perspectives that some educational backgrounds offer. In the context of creativity, being able to take multiple perspectives is what enables individuals to engage in cross-domain integration and recombination of concepts, which forms the basis for creative insights. By emphasizing the importance of having a more multidisciplinary educational background on individuals' ability to become meaningful contributors to digital open innovation initiatives, our findings contribute to the exciting recent work on open innovation that has emphasized the importance of considering characteristics of the individuals involved in open innovation processes.

2. Theoretical background

2.1. Engaging in inbound open innovation through digital crowdsourcing

Recent advances in digital technologies and digitization have greatly facilitated outside-in or inbound open innovation by shifting the locus of many innovation activities outside of the organization (Bogers et al., 2018; Enkel et al., 2009; Nambisan, 2017; Nambisan et al., 2017; West et al., 2014; Yoo et al., 2010; Yoo et al., 2012). Of the different modes by which organizations can organize inbound open innovation, crowdsourcing has been most clearly affected by advances in digitization and digital technology (Pisano and Verganti, 2008). These developments, most notably of Web 2.0, have made it possible for organizations to source innovation tasks to online crowds consisting of thousands of individuals from all over the world and with a wide range of backgrounds and perspectives (Afuah and Tucci, 2012; Brabham, 2013; Howe, 2008; Poetz and Schreier, 2012; West et al., 2014).

While several organizations have organized their own digital crowdsourcing initiatives (e.g. Bayus, 2013; Bjelland and Wood, 2008; Schemmann et al., 2016), others have partnered with specialized online crowdsourcing platforms, such as InnoCentive (for science problem-solving contests), TopCoder (for software contests), 99designs (for design tasks), or Jovoto (for idea generation tasks). Partnering with specialized crowdsourcing platforms allows organizations to direct their open calls at crowds consisting of thousands of individuals who are motivated to contribute to innovation-related tasks, such as the generation of ideas for new products and the solving of specific problems (e.g. Adamczyk et al., 2012; Boons et al., 2015; Zhu et al., 2017). Not only do the crowds that are active on these platforms consist of a large number of potential contributors, more importantly, these crowds are made up of individuals who collectively possess a wide diversity of perspectives that they can bring to bear on innovation-related tasks. By providing organizations access to these large, diverse crowds of individuals, crowdsourcing facilitates "distant searches" for ideas and solutions without incurring the high costs that have traditionally been associated with distant searches (Afuah and Tucci, 2012).

However, while the advances in digitization and digital technologies might facilitate these opportunities for organizations to engage in “distant” searches, organizations now lack the natural limit on their search capacity that in the past had prevented them from looking for contributions among individuals who are so far removed from the organization that they are unlikely to contribute ideas that the organization can actually use (e.g. Dahlander et al., 2016; Katila and Ahuja, 2002; Laursen and Salter, 2006). Such “overreaching” is likely to negatively affect the performance of crowdsourcing initiatives in two important ways: 1) by lowering the *efficiency* of crowdsourcing initiatives because organizations have to spend more time, money, and effort on evaluating ideas that will not turn out to be valuable (Alexy et al., 2012; Bjelland and Wood, 2008) and 2) by lowering the *effectiveness* of a crowdsourcing initiative because organizations target individuals who do not possess a domain-related perspective and are therefore not well-positioned to contribute useful and relevant ideas.

Ignoring this risk of overreaching, proponents of crowdsourcing generally argue that the ability to include individuals who possess different backgrounds and perspectives compared to those held by employees of the organization, lies at the heart of the success of crowdsourcing innovation tasks. Because these individuals possess perspectives that are not directly related to the domain of the tasks that organizations source to the crowd, they are expected to come up with ideas and solutions that are novel to the organization, and hence, valuable (e.g. Boudreau and Lakhani, 2013; Brabham, 2013; Howe, 2008). Studies investigating the novelty of ideas submitted by individuals participating in crowdsourcing have found support for the notion that individuals with unrelated backgrounds and perspectives tend to contribute more novel ideas (e.g. Acar and Van den Ende, 2016; Jeppesen and Lakhani, 2010; Poetz and Schreier, 2012). Poetz and colleagues have found that ‘outsiders’ (i.e. individuals who are expected to possess unrelated perspectives) come up with more novel ideas than ‘insiders’ (i.e. individuals who are expected to possess related perspectives) (Franke et al., 2014; Poetz and Schreier, 2012). Jeppesen and Lakhani (2010) found that technically and/or socially ‘marginal’ solvers, i.e. individuals who are not closely related to the problem domain and “approach the problem with different perspectives and heuristics … not burdened by prior assumptions about effective problem-solving approaches” (Jeppesen and Lakhani, 2010, p. 1017), had a higher chance of coming up with a winning solution in crowdsourced science problem-solving challenges. Finally, individuals with high knowledge distance (i.e. unrelated perspectives) have been shown to outperform individuals with low knowledge distance (i.e. related perspectives) as long as they were highly focused and put in a lot of effort in their creativity process (Acar and Van den Ende, 2016).

The general emphasis in crowdsourcing studies on the benefits of domain-unrelated perspectives, however, contradicts the literatures on creativity and absorptive capacity, which both have emphasized the importance of having a domain-*related* perspective in the innovation process. In the following sections, we use the concept of knowledge schemas from cognitive psychology to develop our theoretical arguments on the different roles that domain-related and domain-unrelated perspectives play in digital crowdsourced innovation tasks.

2.2. The importance of related perspectives in crowdsourced innovation

Cognitive psychology has explored the structures underlying our knowledge bases and perspectives and has found that individuals store domain knowledge in memory in the form of schemas (Dane, 2010; Fiske and Taylor, 1991). These schemas contain “knowledge about a concept or type of stimulus, including its attributes and the relations among those attributes” (Fiske and Taylor, 1991: 98). The more knowledgeable a person is about a certain domain, the more attributes or components will be part of that person's domain schemas and the more linkages there will be between attributes within the schemas and between the schemas (Dane, 2010; Fiske and Taylor, 1991). Individuals create and refine their domain-related schemas through relevant experience and learning about the domain. An individual's formal education is generally considered to be an important foundation for the creation and development of domain-related schemas and differences in the *type* of educational background will affect both the size and complexity of schemas developed in various domains (e.g. Chi et al., 1981). Individuals with a formal education in a certain domain are expected to make much greater use of the schemas related to that domain when making sense of situations and are more likely to activate these schemas when confronted with a creative problem-solving task (e.g. Schwarz et al., 1991).

Indeed, individuals with a degree in Engineering or Science have been shown to focus on different aspects of the product development process than individuals with a Business or Economics background (e.g. Griffin and Hauser, 1992, 1996). In this context, Silva and colleagues (2018) showed that engineering students focused on product functionality, often at the expense of doing proper market research, while business students focused more on the marketability of the product and less on product functionality. These differences also affected performance. Zhu and colleagues (2017) found that engineering expertise was related to higher likelihoods of bringing a product to market, while marketing expertise was related to higher sales. Whether or not individuals have a domain-related educational background, and thus can activate larger and more complex schemas with regard to the problem domain, is likely to play an important part in determining how individuals perform on idea generation tasks and whether their ideas will have the potential to turn into successful innovations.

Schemas play a critical role in the initial stages of the creative problem-solving process, which involve recognizing, defining, and representing of the problem (Amabile, 1996; Lubart, 2001; Newell and Simon, 1972; Pretz et al., 2003). In these initial stages, schemas are activated to provide a creative problem solver with a framework for understanding a problem and assessing the appropriateness of different problem representations (Berg, 2014; Wiley, 1998). Essentially, idea generators' perspectives, i.e. their internal representation of the problem, are driven by their existing schemas related to the problem domain, which means individuals define and represent the task in terms of what they already know (Hong and Page, 2001).

Individuals with a domain-related perspective (often provided by having an education related to the domain of the task) are likely to have larger and more complex schemas related to the problem domain. The larger and more complex these schemas are with respect to the domain of a certain problem, the easier it is for solvers to understand the problem and decide on an appropriate problem representation (e.g. Chi et al., 1981; Fiske and Taylor, 1991). Being able to take a *related* perspective thus improves an individual's ability to identify ideas that will be useful and relevant for organizational innovation. Without first having an appropriate understanding of the ideation task, it is unlikely that individuals can subsequently develop good solution strategies that will provide useful and relevant ideas and solutions (Pretz et al., 2003; Hong and Page, 2001). For this reason, a domain-related background is generally considered a necessary prerequisite for good performance on a creative task (Amabile, 1996; Woodman et al., 1993). Indeed, when comparing experts to novices, the main difference is that they typically differ in how they define and represent problems (Chi et al., 1981; Dane, 2010; Fiske and Taylor, 1991; Lesgold, 1988).

Another stream of literature that speaks to the role of related knowledge backgrounds in innovation is the absorptive capacity literature. This literature poses that organizational innovation depends upon both a supply of novel ideas and the ability of the organization's employees to recognize their value and integrate them – an organization's absorptive capacity (Cohen and Levinthal, 1990). Absorptive capacity studies have emphasized the importance of organizations being able to relate ideas from external contributors to their existing knowledge base and understand how to make use of the contributions (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998; Schweisfurth and Raasch, 2018; Zhu et al., 2017). In the context of open innovation, organizational employees' levels of education and their educational diversity have been found to affect their ability to identify and absorb external knowledge (e.g. Ahn et al., 2017; Bogers et al., 2018; Østergaard et al., 2011). Essentially, this means that external contributors perform better in crowdsourced innovation-related tasks if they can communicate their ideas in ways that are more closely related to the domain schemas held by members of the crowdsourcing organization (Newell and Simon, 1972; Pretz et al., 2003). Indeed, Piezunka and Dahlander (2015) found that the most novel ideas from people with perspectives that are not directly related to a problem at hand were less likely to get the attention they needed from the crowdsourcing organization's employees to get developed further.

Taken together, individuals participating in crowdsourced idea generation tasks are thus likely to benefit from having an educational background that is related to the domain of the task because they will have larger and more complex schemas related to the domain. These schemas will allow them to better understand the problem and identify a relevant problem representation (Chi et al., 1981; Newell and Simon, 1972; Pretz et al., 2003). In addition, when the schemas of individuals participating in crowdsourced idea generation tasks are more similar to those of members of the crowdsourcing organization, these external contributors are better able to communicate their ideas in a way that the organization understands, which allows the organization to recognize the value of the ideas and make use of them (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998; Piezunka and Dahlander, 2015). We therefore hypothesize that:

Hypothesis 1. Ideas from individuals with an educational background related to the domain of the idea generation task will perform better in a crowdsourced idea generation task than ideas from individuals with an educational background that does not offer a related perspective.

At this point, it is important to note that (in our study context) every individual has some form of educational background. As a result, if their educational background does not provide individuals with a related perspective, this implies that these individuals will have (only) an unrelated perspective. We have so far argued that related perspectives play a crucial role in understanding a problem, defining a problem representation, and communicating a solution in a way that the crowdsourcing organization understands and this meant that such benefits are not apparent for individuals with only unrelated educational backgrounds. Yet, this does not imply that there are no benefits to being able to tap into unrelated perspectives. In the following section we develop our argument that being able to take an unrelated perspective may provide its own benefits, but these benefits only materialize into better performance in combination with a related perspective.

2.3. The importance of unrelated perspectives in crowdsourced innovation

Unrelated perspectives have been argued to play a crucial role in the later stages of the idea generation process where individuals develop a solution strategy and try to generate creative ideas "by inventing a creative solution" (Poetz and Schreier, 2012, p. 245). Essentially, the process of inventing a creative solution consists of integrating and recombining the concepts in solvers' existing schemas in new ways (Fleming, 2001; Katila and Ahuja, 2002; Mumford and Gustafson, 1988). The more incremental ideas and insights are the result of individuals recombining concepts within or across schemas related to the domain, requiring (only) related perspectives. Yet the more novel insights are based on integrations and recombinations made between schemas related to the problem domain and schemas unrelated to the domain (Mumford and Gustafson, 1988). Thus, novelty is the potential benefit of being able to make use of unrelated perspectives (i.e. having well-developed schemas from outside of the domain).

Indeed, compared to individuals who only have a related educational background, individuals who possess an educational background that also provides perspectives unrelated to a certain problem domain can make use of a larger variety of schemas. These knowledge schemas that are not related to the domain might also be large and complex, thereby providing such individuals with more diverse material to work with. Key here, however, is individuals' ability to integrate and recombine concepts from different (i.e. related and unrelated) domains. Ideas and solutions based on perspectives from one domain cannot readily be applied to a different domain without adjusting it to specific characteristics of the idea challenge at hand. Making connections between two different fields thus requires considerable knowledge about both fields (Fleming, 2001). A related perspective not only allows individuals to better understand the task and come up with useful and relevant ideas for the organization, but also plays an important role in correctly adjusting ideas and solutions from a different task domain to be relevant for the task domain (Amabile, 1996; Weisberg, 1998). Idea generators who have an educational background that allows them to take unrelated perspective(s) in addition to their domain-related perspective are thus expected to be better able to take insights from one domain and apply it to an ideation task in another domain (Berg, 2014; Luo and Toubia, 2015), allowing for ideas that are both novel and useful, and therefore valuable for crowdsourcing organizations (e.g. Schweisfurth, 2017). Importantly, such benefits do not generalize to individuals who have only an unrelated (but no related) background. Indeed, possessing unrelated perspectives is expected to be an important addition to the positive relationship between a related perspective and the performance of participants on crowdsourced innovation-related tasks, because individuals with a domain-related perspective are expected to be able to take the novel insights that domain-unrelated perspectives allow for and translate them into useful and relevant ideas for the organization (Berg, 2014; Dahlander et al., 2016). We therefore hypothesize that:

Hypothesis 2. Ideas contributed by individuals who possess a related perspective to the domain of the idea generation task will be associated with better performance when combined with an unrelated perspective than when they are not combined with an unrelated perspective.

Combining our two hypotheses, we thus expect individuals with no related perspective (i.e. only an unrelated perspective) to have the lowest performance (they do not enjoy the benefits of related perspectives while the potential benefits of having an unrelated perspective are unlikely to materialize due to lack of a related perspective). We expect individuals who have both a related and an unrelated perspective to do better than individuals with only a related perspective (the former, as compared to the latter, enjoy the potential benefits of having an unrelated perspective which are also likely to materialize given the related perspective).

3. Data and methods

3.1. Research context

Data was collected from the largest Dutch online crowdsourcing platform for idea generation tasks. The crowdsourcing platform acts as an intermediary between external "seeker" organizations and its member community of "solvers" (Brabham, 2013; Howe, 2008; Jeppesen and Lakhani, 2010). These idea generation tasks were framed as challenges to the members of the crowdsourcing platform to come up with idea proposals for new products and services and/or how to improve an organization's current offerings (see also Bayus, 2013; Boons et al., 2015; Schemmann et al., 2016). Examples of such challenges were "Come up with new ideas for recycling of old oil and gas platforms or parts of them" and "How can social media help entrepreneurs start their own companies". Challenges were presented in the form of briefings, which consisted of an introduction of the organization and the issue at hand, the main question members need to address, and some relevant background information about the challenge, such as the total prize pool, the proposed distribution of monetary rewards among the best contributions, and submission deadline. In the sense that members worked on tasks individually and submitted ideas that competed for rewards, this was a form of "tournament-based crowdsourcing" (Afuah and Tucci, 2012, p. 355; Majchrzak and Malhotra, 2016). While the platform had no formal requirements for the layout of the idea proposals, most idea proposals were quite elaborate documents, generally between 3 and 5 pages, which often included graphical representations and additional information to support the main innovation idea.

The online crowdsourcing platform specifically targeted students and young professionals up to 32 years old from a single country (The Netherlands). Only a few participants of the challenges on this platform had substantial work experience and nearly all of them had or were pursuing their education at one of the Dutch universities. This context therefore allowed us to use educational background as a meaningful, objective proxy for the perspectives that participants could bring to bear on a given idea challenge. Furthermore, the nature of the idea challenges was such that, unlike more specialized tasks such as scientific problem-solving tasks that are hosted on InnoCentive, participants did not need to possess advanced knowledge to contribute an idea (e.g. Bayus, 2013; Boons et al., 2015; Schemmann et al., 2016). This allowed us to compare the performance of individuals with and without an educational background that offered a domain-related perspective.

After the submission deadline of a challenge, the submitted idea proposals were ranked by the crowdsourcing organization and the winning ideas were rewarded with a monetary reward ranging from €50 up to €3000. On the crowdsourcing platform ideas were ranked and rewarded as follows: the winner (rank 1) would receive 30% of the overall prize pool, the runner-up (rank 2) would receive 15% of the prize pool, the second runner-up (rank 3) would receive 7% of the prize pool, a top 10 idea (rank 4–10) would receive 4% of the prize pool, and a top 20 idea (rank 11–20) would receive 2% of the total prize pool. In 87.5% of the cases the prize pool contained the 'standard' €5000 (min: €3000; max: €10,000).

3.2. Data collection procedure

Data were collected from three sources. First, data on the participation and performance of members on the idea challenges that had been completed were collected from the website of the crowdsourcing platform. For each challenge, we were able to retrieve information on the names of the members who submitted the idea proposals and the ranking of the ideas. Second, the crowdsourcing platform provided us with access to their database, which contained detailed information about the demographic background of its members, including their education, as well as data on member activity on the platform. Finally, we analyzed the detailed challenge briefings, which were retrieved from the website of the crowdsourcing platform, and coded information on submission deadlines, total prize pools, and the distribution of monetary rewards.

3.3. Study sample

At the time of data collection, the organization had been in existence for 4.5 years and 135 idea challenges had been successfully completed. Of these 135 challenges, we did not include 15 challenges that were either part of the start-up phase of the crowdsourcing platform (9) or did no offer monetary rewards (6). Based on a discussion about the topics of the idea challenges between the first author and a representative of the crowdsourcing platform, it was decided to identify 3 main categories of idea challenges: 'Business', 'Technical', and 'Other'. Two coders independently coded the full briefings of 120 challenges. Their first coding had an inter-rater agreement of .71 for Randolph's free-marginal multi-rater kappa, which was found to be adequate (Cohen, 1960; Gwet, 2012; Warrens, 2010). In the case of a disagreement the coders discussed the challenge briefing with a representative from the crowdsourcing platform and then agreed on a final coding. In the end, the coders classified 39 challenges (32.5%) as 'Business' challenges. An example of a 'Business' challenge was "How can [company] involve customers in innovating bicycles". 29 challenges (24.2%) were classified as 'Technical', such as "Design a bicycle parking area that takes into account the diversity of bicycles". The remaining 52 challenges (43.3%) had a more general orientation that did not deal with a specific domain. An example challenge that was coded as 'Other' was "Come up with ideas to reduce loneliness amongst young adults". Because we were interested in the match between the challenge orientation and the educational background of idea contributors, we included the 68 challenges that were coded as either 'Business' or 'Technical' in our main study sample.

For this study we included members who had logged in at least once after the day they had registered as a member of the platform and we excluded 231 members (5.0%) for whom we did not have complete information about their educational backgrounds. Of the remaining 4365 members, the average age was 23.45 years (sd = 3.13), 70% were male, and 55% had (or were pursuing) a university-level degree. In terms of educational backgrounds, 33% had (or were pursuing) a Business and Economics-oriented degree and 28% a Science and Technology-oriented degree (see the measures section for more details). Because we were interested in the match between the challenge orientation and the educational background of idea contributors, we included all 2669 individuals who were coded as having an educational background that at least offered them a 'Business and Economics' perspective or a 'Science and Technology' perspective in our preliminary analyses to check whether there was a self-selection bias in our data. In total, of the 2669 members in our main study sample, 948 members submitted 2178 individual idea proposals to 68 challenges. These 2178 individual idea proposals formed the dataset of our main analyses. On average, the 68 challenges received 32.03 individual contributions from the members in our main study sample (min: 15; max: 69) and in total €209,700 was awarded to these 2178 individual contributions.

3.4. Measures

Crowdsourcing organizations are specifically seeking to innovate so are looking for creative ideas and suggestions that are both novel and useful for the organization. For this reason, the individuals in the crowdsourcing organization who would be responsible for using and integrating the ideas in the organization's innovation process are best positioned to assess the value of individual ideas and suggestions (e.g. Bayus, 2013; Piezunka and Dahlander, 2015; Schemmann et al., 2016). In line with previous research (see also Acar and Van den Ende, 2016; Jeppesen and Lakhani, 2010), we therefore used the ranking of the idea proposals by the crowdsourcing organization as our measure of *idea performance*. Contributions were ranked as follows: 1st, 2nd, 3rd, 4th-10th (no distinction was made between the exact ranks), 11th–20th (no distinction was made between the exact ranks), and not ranked in the top 20. Additionally, we used an alternative operationalization of performance, *challenge winner*, in which we coded whether a contribution belonged to the best 20 idea proposals of a challenge or not (0 = no; 1 = yes). Because members could participate in more than one challenge, to correctly model the panel nature of our dataset we used random-effects ordered probit models for the analyses on the *idea performance* dependent variable and a random-effects probit model for the *challenge winner* dependent variable (Wooldridge, 2002).

To code whether members possessed related and/or unrelated perspectives with regard to a particular challenge, we used the information that was provided by participants about their educational background when they signed up as a member of the online crowdsourcing platform (for a similar approach see also Dahlin et al., 2005). Because the crowdsourcing platform specifically targeted students and young professionals up to 32 years old, we consider participants' formal educational disciplines to be a good reflection of the perspectives they can bring to bear on the idea generation tasks. Based on the information on members' educational backgrounds, a list of several hundred disciplines was generated. In consultation with two educational experts at the first author's university, each entry on this list was subsequently coded into categorical variables that indicated whether the educational discipline allowed for a 'Business and Economics' perspective or a 'Science and Technology' perspective, in line with previous research on different backgrounds in R&D contexts (see also Ahn et al., 2017; Bobadilla and Gilbert, 2017; Griffin and Hauser, 1992, 1996; Silva et al., 2018; Zhu et al., 2017). If a discipline offered neither a 'Business and Economics' nor a 'Science and Technology' perspective, such as for example law or medicine, the educational background was coded as 'Other'. A single educational discipline could offer multiple perspectives, such as in the case of the discipline "Economics and Law", which was coded as offering both a 'Business and Economics' perspective and an 'Other' perspective. Based on the educational discipline(s) a member (had) pursued, we thus coded their perspectives. In the cases in which a member combined multiple disciplines (members could self-report up to 4 disciplines on the platform), we used all their educational disciplines to code their perspectives. Overall, 53.8% of the members in our sample had (or were pursuing) an educational discipline with a 'Business and Economics' perspective, 46.5% an educational discipline with a 'Science and Technology' perspective, and 19.8% an educational discipline with a perspective that was coded as 'other'. In total, 20.2% of the individuals in our sample had (or were pursuing) an educational discipline that offered multiple perspectives.

The coding of educational backgrounds into perspectives allowed us to consider whether there was a match between an individual's perspectives and the content domain of each challenge on the crowdsourcing platform. In the cases where members with an educational background that offered only a 'Business and Economics' perspective could participate in a challenge with a 'Business' orientation and in the cases where members with an educational background that offered only a 'Science and Technology' perspective could participate in a challenge with a 'Technical' orientation, the member possessed a perspective that is related to the domain of the task. In such cases, we coded the member-challenge combinations as possessing only a related perspective (*only related perspective* = 1). In the cases where members without a 'Business and Economics' perspective would participate in a challenge with a 'Business' orientation and in the cases where members without a 'Science and Technology' perspective would participate in a challenge with a 'Technical' orientation, then the member possessed only a perspective that is unrelated to the domain of the task. In such cases, we coded the member-challenge combinations as possessing only an unrelated perspective (*only unrelated perspective* = 1). In the cases that a member possessed both a related and an unrelated perspective with regard to a particular challenge we coded the member-challenge combination as possessing both a related and an unrelated perspective (*related & unrelated perspective* = 1). We note that, given the coding scheme described above, with regard to each challenge a member's perspective has been coded as either *only unrelated perspective* (N = 1074; 49.3%), or *only related perspective* (N = 799; 36.7%), or *related & unrelated perspective* (N = 305; 14%). In reporting the results, we use having *only an unrelated perspective* as the baseline to which we statistically compare the effects of having *only related perspective* or having both *related & unrelated perspective*.

We included several control variables in all our analyses; At the level of the challenge, we control for the total *number of submissions* to the challenge, because the more idea proposals are submitted the more competition any individual idea proposal experiences. At the level of the individual, we control for a member's *age*, *sex* (male = 0; female = 1), *education level* (university of applied science = 0; university = 1), whether the member was combining *multiple disciplines*, and whether the member had already *registered before the study period* with the crowdsourcing platform. We also controlled for the fact if members had *graduated* (no = 0; yes = 1) at the time of a challenge to control for potential in-job training effects. Additionally, we controlled for the number of challenges that the member had previously participated in (*challenge experience*) and how well they had performed in previous idea challenges on the platform by calculating their average winnings per challenge up until that challenge (*average previous performance*).

3.5. Estimation strategy

A key characteristic of digital crowdsourcing innovation platforms is the fact that participation in challenges is completely voluntary (e.g. Afuah and Tucci, 2012; Brabham, 2013; Jeppesen and Lakhani, 2010). In the context of idea generation tasks, members are expected to participate on those challenges that they expect to perform well on. This means that the decision to participate on an idea generation challenge is not random but based on inherent characteristics of individual members, such as their educational background. Any statistical analysis of members' performance on crowdsourced innovation tasks that does not take into account this self-selection by individuals might well result in biased estimates (see also Jeppesen and Lakhani, 2010). We therefore first performed Heckman selection models (Chiburis and Lokshin, 2007; De Luca and Perotti, 2011; Heckman, 1979; Van de Ven and Van Praag, 1981) to account for potential sample selection bias in our main analyses. In the first stage of these Heckman selection models, we estimated how our variables of interest affected the chance that a particular member contributed an idea proposal to a particular challenge. In the second stage, we subsequently estimated how our variables of interest affected the performance of members on the challenges in which they have participated, controlling for potential self-selection into a particular challenge based our variables of interest. Importantly, because members can participate in multiple challenges (the number of challenges they can participate in depends on when they signed up) our data is essentially multilevel data and in order to take this into account in a Heckman model, we clustered standard errors by member (Wooldridge, 2002). Because the results of these Heckman selection models indicated that our estimates of how our variables of interest affected the performance of members on the challenges in which they have participated were not biased by self-selection effects, we decided to report the results of these Heckman selection models as robustness analyses (models 3 and 4 in Table 4) and instead report the results of a random-effects ordered probit model and random-effects probit model (Wooldridge, 2002) that both can fully account for the unbalanced panel nature of our dataset as our main analyses (models 1 and 2 in Table 3).

4. Results

4.1. Descriptive statistics

We conducted preliminary analyses of the descriptive statistics and correlations among the variables in our main analyses. We included all contributions (N = 2178) that were made by individual members (N = 948) to the 68 challenges in our study sample (see Table 1 for the means, standard deviations and Table 2 for the zero-order correlations of the variables in our main analyses).

Concerning our variables of interest, we note that individuals had an educational background that offered them only a related perspective in 49.3% of the cases and only an unrelated perspective in 36.7% of the cases. Of the 2178 contributions a total of 305 (14.0%) concerned cases in which individuals had an educational background that offered them both a related and an unrelated perspective with regard to the challenge at hand. In line with our expectations, the correlation coefficients of having *only related perspective* were positive (ρ = 0.040 for *idea performance* and ρ = 0.055 for *challenge winner*), while the correlation coefficients of having *only unrelated perspective* were negative for both performance measures (ρ = −0.089 for *idea performance* and

Table 1
Descriptive Statistics of Measures.

Variables	Mean	sd	Min	Max
Idea Performance	96.281	235.313	0	1500
Challenge Winner (Top 20)	0.378	0.485	0	1
Only Related Perspective	0.493	0.500	0	1
Only Unrelated Perspective	0.367	0.482	0	1
Related & Unrelated Perspective	0.140	0.347	0	1
Age	23.555	3.027	17	32
Sex	0.191	0.393	0	1
Education Level	0.724	0.447	0	1
Multiple Studies	0.023	0.150	0	1
Graduated	0.272	0.445	0	1
Challenge Experience	4.098	6.881	0	55
Average Previous Performance (ln)	2.350	2.451	0	7.314
Registered Before Study Period	0.145	0.352	0	1
Number of Submissions	60.771	24.141	27	122

n = 2178.

Table 3
Main Analyses.

	Model 1		Model 2	
	DV: Idea Performance		DV: Challenge Winner (Top 20)	
	Random Effects Ordered Probit		Random Effects Probit	
	Coefficient	Robust standard error	Coefficient	Robust standard error
Independent variables:				
Only Related Perspective[a]	0.235	0.061***	0.242	0.065***
Related & Unrelated Perspective[a]	0.428	0.098***	0.412	0.099***
Control variables:				
Age	0.051	0.013***	0.038	0.014**
Sex	−0.095	0.084	−0.147	0.084
Education Level	0.227	0.073**	0.234	0.072***
Multiple Studies	0.147	0.238	0.247	0.295
Graduated	−0.099	0.088	−0.091	0.096
Challenge Experience	−0.008	0.005	−0.007	0.005
Average Previous Performance (ln)	0.033	0.015**	0.049	0.016**
Registered Before Study Period	0.061	0.103	0.089	0.111
Number of Submissions	−0.014	0.001***	−0.015	0.001***
Constant	–	–	−0.759	0.320*
Cut Point 1	1.105	0.312	–	–
Cut Point 2	1.736	0.312	–	–
Cut Point 3	2.541	0.313	–	–
Cut Point 4	2.780	0.313	–	–
Cut Point 5	3.102	0.314	–	–
Wald chi-square	168.50***		182.65***	
Number of clusters	948		948	
Number of observations	2178		2178	

[a] in models 1 and 2 the baseline comparison group is individuals who have an educational background that only offered them an unrelated perspective.
*** $p < .001$.
** $p < .01$.
* $p < .05$.

ρ = −0.106 for *challenge winner*). Having both *related & unrelated perspective* was positive and significant for both performance measures (ρ = 0.067 for *idea performance* and ρ = 0.068 for *challenge winner*).

4.2. Main analyses

In order to test our hypothesis, we performed random-effects (ordered) probit analyses, which fully account for the unbalanced panel nature of our dataset, in which we considered the performance effects of *only related perspective* and *related & unrelated perspective* (relative to the baseline case of *only unrelated perspective*), controlling for the previously identified control variables.

In model 1, we performed a random-effects ordered probit model as *idea performance* was operationalized as a rank-ordered variable. Overall, the Wald chi-square was significant ($\chi^2(11) = 168.50$, $p < .001$), which indicates good model fit (Greene, 2003). In this analysis, a number of control variables appeared to have an influence on idea performance (see Table 3). A member's age ($\beta = 0.051$, $p < .001$), education level ($\beta = 0.227$, $p < .01$), and previous performance ($\beta = 0.033$, $p < .01$) were positively related to idea performance, while the number of submissions ($\beta = -0.014$, $p < .001$) was negatively related to idea performance. Considering our variables of interest, we see that, in support of hypothesis 1, ideas contributed by individuals who had *only a related perspective* performed significantly better ($\beta = 0.235$, $p < .001$) than ideas contributed by compared to members without a related perspective (the baseline comparison group is *only unrelated perspective*). Ideas by participants with educational backgrounds that offered them both a *related and an unrelated perspective* had an even stronger significantly positive effect ($\beta = 0.428$, $p < .001$). In support of hypothesis 2, the difference between individuals with *only a related perspective* and individuals with both a *related and an unrelated perspective* was statistically significant ($\beta_{diff} = 0.193$, $p < .05$).

In model 2 we examined the same relationships, but we operationalized performance not as a ranking variable, but simply measured whether contributions were challenge winners. A contribution is

Table 2
Correlations of measures included in idea performance analyses.

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. Idea Performance	–													
2. Challenge Winner (Top 20)	0.525	–												
3. Only Related Perspective	0.040	0.055	–											
4. Only Unrelated Perspective	−0.089	−0.106	−0.751	–										
5. Related & Unrelated Perspective	0.067	0.068	−0.398	−0.307	–									
6. Age	0.137	0.085	−0.072	0.017	0.080	–								
7. Sex	−0.001	−0.041	−0.020	0.007	0.020	0.096	–							
8. Education Level	0.071	0.096	−0.034	0.042	−0.008	0.124	0.062	–						
9. Multiple Studies	0.002	0.039	−0.114	0.004	0.159	−0.031	0.027	0.033	–					
10. Graduated	0.104	0.043	−0.047	0.013	0.051	0.662	0.119	0.070	−0.052	–				
11. Challenge Experience	0.080	0.097	−0.033	0.007	0.038	0.301	−0.017	0.082	0.045	0.292	–			
12. Average Previous Performance (ln)	0.125	0.166	0.002	−0.021	0.027	0.213	−0.010	0.121	0.061	0.192	0.531	–		
13. Registered Before Study Period	0.065	0.057	0.015	0.012	−0.038	0.117	−0.060	0.052	0.007	0.136	0.102	0.056	–	
14. Number of Submissions	−0.142	−0.266	−0.085	0.051	0.053	−0.003	0.028	−0.066	0.007	0.006	−0.080	−0.130	−0.035	–

n = 2178; all correlations larger than 0.042 are significant at $p < .05$.

Table 4
Robustness Analyses.

	Model 3		Model 4		Model 5	
	DV: Idea Performance		DV: Challenge Winner (Top 20)		DV: Idea Performance (Tech)	
	Ordered Probit Heckman		Probit Heckman		Random Effects Ordered Probit	
	Coefficient	Robust standard error	Coefficient	Robust standard error	Coefficient	Robust standard error
Second stage: Performance						
Independent variables:						
Only Related Perspective[a]	0.221	0.061***	0.219	0.066***		
Related & Unrelated Perspective[a]	0.407	0.094***	0.400	0.098***	0.330	0.124**
Control variables:						
Age	0.042	0.012***	0.033	0.013*	0.081	0.025***
Sex	−0.096	0.078	−0.144	0.081	−0.600	0.191**
Education Level	0.200	0.067**	0.204	0.070**	0.092	0.132
Multiple Studies	0.112	0.191	0.219	0.262	0.132	0.333
Graduated	−0.046	0.086	−0.066	0.094	−0.312	0.153*
Challenge Experience	−0.005	0.005	−0.005	0.006	−0.010	0.008
Average Previous Performance (ln)	0.048	0.016***	0.054	0.018**	0.053	0.028
Registered Before Study Period	0.142	0.100	0.124	0.106	0.015	0.187
Number of Submissions	−0.013	0.001***	−0.015	0.001***	−0.015	0.002***
Constant	–	–	−0.421	0.440	–	–
First stage: Challenge Participation						
Independent variables:						
Only Related Perspective[a]	0.193	0.025***	0.193	0.025***		
Related & Unrelated Perspective[a]	0.384	0.042***	0.384	0.041***		
Control variables:						
Age	0.002	0.006	0.002	0.006		
Sex	0.009	0.035	0.009	0.035		
Education Level	−0.009	0.031	−0.009	0.031		
Multiple Studies	0.115	0.128	0.115	0.128		
Graduated	−0.196	0.042***	−0.196	0.042***		
Challenge Experience	0.050	0.004***	0.050	0.004***		
Average Previous Performance (ln)	0.103	0.008***	0.103	0.008***		
Prize Amount (ln)	0.001	0.073	0.002	0.073		
Platform Year 1	1.154	0.060***	1.154	0.060***		
Platform Year 2	0.408	0.034***	0.408	0.034***		
Platform Year 4	−0.164	0.036***	−0.164	0.036***		
Platform Year 5	−0.249	0.053***	−0.249	0.053***		
Registered Before Study Period	−0.429	0.041***	−0.429	0.041***		
Constant	−2.381	0.629***	−2.388	0.629***		
Cut Point 1	0.721	0.414	–	–	1.363	0.576
Cut Point 2	1.314	0.417**	–	–	2.010	0.584
Cut Point 3	2.290	0.425***	–	–	2.857	0.588
Cut Point 4	2.593	0.424***	–	–	3.097	0.598
Cut Point 5	3.102	0.426***	–	–	3.425	0.603
Wald chi-square	162.92***		167.94***		87.39***	
Wald chi-square for indep. equations	0.91^{ns}		0.73^{ns}		–	
Number of observations (Stage 1)	106,813		106,813		–	
Number of clusters (Stage 1)	2669		2669		–	
Number of censored observations	104,635		104,635		–	
Number of uncensored obs. (Stage 2)	2178		2178		658	
Number of clusters (Stage 2)	–		–		354	

Note. In models 3 and 4 robust standard errors are clustered around individuals.
[a] in models 3 and 4 the baseline comparison group is individuals who have an educational background that only offered them an unrelated perspective.
*** $p < .001$.
** $p < .01$.
* $p < .05$.

considered a challenge winner if the contribution is ranked in the top 20 and thus received a monetary reward. As *challenge winner* is a binary outcome variable, we use a random-effects probit analysis to fully account for the unbalanced panel nature of our dataset and the nature of the dependent variable. Overall, the Wald chi-square was significant ($\chi^2(11) = 182.65$, $p < .001$), which indicates good model fit (Greene, 2003). In line with the results from the random-effects ordered probit model, both the probit coefficients of *only related perspective* ($\beta = 0.242$, $p < .001$) and having a *related and unrelated perspective* were significantly positive ($\beta = 0.412$, $p < .001$). The difference between individuals with *only a related perspective* and individuals with both a *related and an unrelated perspective* was also marginally statistically significant ($\beta_{\text{diff}} = 0.170$, $p = .085$).

4.3. Robustness analyses

We performed several additional robustness analyses (see models 3–5 in Table 4) to verify that our findings were robust to different methodological and sampling decisions. First of all, we present the Heckman self-selection models we initially ran to statistically test whether our performance analyses might be affected by self-selection bias. For all eligible members with at least an educational background in 'Business and Economics' and/or 'Science and Technology' ($N = 2669$) we coded whether or not each member contributed to a particular challenge by means of a dummy variable called *challenge participation*. We used this variable as the dependent variable of the first stage of the Heckman selection models. Given that not all members

Table 5
Margin estimates of performance levels for random-effects ordered probit model.

Prediction	Only Unrelated		Only Related		Related and Unrelated	
	Margin	Robust Std. Err.	Margin	Robust Std. Err.	Margin	Robust Std. Err.
Outcome = 0	0.697	0.016***	0.621	0.016***	0.555	0.032***
Outcome = 100	0.162	0.009***	0.186	0.009***	0.202	0.011***
Outcome = 200	0.105	0.009***	0.136	0.008***	0.164	0.015***
Outcome = 350	0.014	0.003***	0.021	0.003***	0.027	0.005***
Outcome = 750	0.011	0.003***	0.018	0.002***	0.024	0.005***
Outcome = 1500	0.011	0.003***	0.018	0.002***	0.028	0.006***

*** $p < .001$.

could participate on all challenges (as they might not have been registered on the crowdsourcing platform yet), we only included those member-challenge combinations that members were able to participate in ($N = 106{,}813$). We added additional control variables to account for factors that were likely to affect the likelihood of a challenge being participated in by members. In addition to the control variables we included in the main analyses, we controlled for the natural logarithm of the total *prize amount* made available for the challenge and the year of operation in which the challenge took place (by including *platform year* dummies in which year 1 refers to the first year of operation of the platform, et cetera). We also clustered error terms within individuals to correct for the fact that individuals were able to participate and perform in multiple challenges in our dataset (Wooldridge, 2002). The results of the two Heckman self-selection models showed that for neither of the two performance measures self-selection seemed to affect our results as these models showed an insignificant Wald chi-square for independent equations (Model 3: $\chi^2(1) = 0.91, ns$; Model 4: $\chi^2(1) = 0.73, ns$).

Considering the results of our main variables of interest, individuals were more inclined to contribute to challenges for which their educational background offered them a related perspective (*only related perspective*: $\beta = 0.193$, $p < .001$; *related and unrelated perspective*: $\beta = 0.384$, $p < .001$). With regard to both our performance measures, the results of the second stage of the Heckman selection models were in line with the results reported in the random-effects (ordered) probit models; members who participated in challenges for which their educational backgrounds offered them *only a related perspective* performed significantly better than members who participated in challenges for which their educational backgrounds did not offer them a related perspective (DV *idea performance*: $\beta = 0.221$, $p < .001$; DV *challenge winner*: $\beta = 0.219$, $p < .001$), while members with educational backgrounds that offered them both a *related and unrelated perspective* performed significantly better than possessing only an unrelated perspective (DV *idea performance*: $\beta = 0.407$, $p < .001$; DV *challenge winner*: $\beta = 0.400$, $p < .001$) and significantly better than possessing *only a related perspective* (DV *idea performance*: $\beta = 0.186$, $p < .05$; DV *challenge winner*: $\beta = 0.181$, $p < .05$).

Secondly, because our results might, at first glance, be interpreted as showing the opposite of what Jeppesen and Lakhani (2010) found in their analysis of science problem-solving contests at InnoCentive, we also analyzed a subset of our data that was an approximation of the sample used in their study, namely a sub-sample of the 29 ‘Technical’ challenges and those individuals that had at least an educational background with a ‘Science and Technology’ orientation. We ran a random-effects ordered probit model to take into account the panel nature of our dataset and the fact that our dependent variable was rank-ordered (see model 5 in Table 4). The results of this model showed that being able to bring unrelated perspectives to bear on a challenge contributes significantly and positively to performance if combined with an educational background that offers you also a related perspective (model 5: $\beta = 0.330$, $p < .01$). The results of our study were thus in line with the findings of the study by Jeppesen and Lakhani (2010), but by studying crowdsourced idea generation tasks that do not implicitly require participants to also have related perspectives, we were able to empirically test the effect of having a related educational background versus lacking one.

4.4. Economic impact analyses

To understand what the economic impact was for participants with regard to how their educational backgrounds related to the crowdsourced idea generation task, we used the estimates of the random-effects ordered probit analysis (model 1) to calculate the likelihood that the contribution of a participant with a certain perspective would be ranked at a certain rank. A contribution on this crowdsourcing platform could be ranked at six different levels: 1st, 2nd, 3rd, 4th-10th, 11th-20th, or not ranked in the top 20. If a contribution was not ranked in the top 20, participants would not receive a reward for their efforts. For our impact analysis, we assigned rewards to the top 20 contributions of each challenge according to the fixed reward schema the platform used and based on the most prevalent total reward amount (57 out of 68 challenges offered €5000 in total rewards). Based on this assignment, rank 1 was assigned €1500, rank 2: €750, rank 3: €350, ranks 4–10: €200, and ranks: 11–20 €100. We then used the results of the random-effects ordered probit model (model 1) to calculate margin estimates for each of these outcomes (see Table 5).

Considering the performance of the different groups, we can see that participants who could only use an unrelated perspective, on average, were expected to earn €66.82 when they submitted an idea. Participants who had an educational background that offered them a related perspective, on average, were expected to earn €93.90 per idea submission. While participants who had an educational background that offered them both a related perspective and an unrelated perspective on the idea task at hand, on average, were expected to earn €122.32 when they submitted an idea. Compared to contributions of members with only an unrelated perspective, participants with only a related educational perspective, on average, earned €27.08 more per contribution (a difference of 40.5%) and participants who had an educational background that allowed them to tap into both related and unrelated perspectives, on average, earned €55.50 more per contribution than individuals without a related perspective (a performance difference of 83.1%) and €28.42 (or 30.3%) more than individuals with only a related perspective.

Finally, looking more closely at the results in Table 5, one can see that one part of the explanation for this better average performance is that the chances of being a winner of any reward are lower for participants with only an unrelated perspective (30.3%) compared to participants with only a related perspective (37.9%) and compared to participants with an educational background that allowed them to tap into both a related and unrelated perspective (44.5%). However, organizations might be more interested in understanding how individuals' educational backgrounds affected the generation of the very best solutions (e.g. Fleming, 2007; Girotra et al., 2011; Lettl et al., 2009). A visualization of the results of Table 4 shows that the chances of being in a higher performance category were increasingly higher for participants with an educational background that allowed them to tap into both a related and unrelated perspective compared to participants with only a related or an unrelated perspective (see Fig. 1).

Participants with an educational background that allowed them to tap into both a related and an unrelated perspective were 51% more likely to have their ideas ranked as the best idea compared to individuals with only a related perspective and 158% more likely than individuals lacking a related perspective.

Taken together, our findings lend strong support to hypothesis 1 by showing that ideas contributed by individuals with *only a related perspective* and by individuals with a *related & unrelated perspective* performed significantly better than ideas contributed by individuals

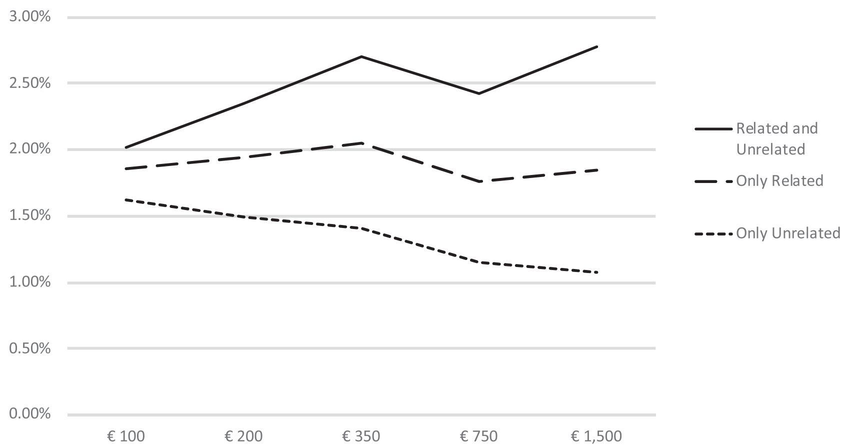

Fig. 1. Relative chances of winning a prize per category.
Note. In this visualization, we have adjusted the margin estimates for the categories €100 and €200 to take into account that multiple ideas are rewarded €100 and €200.

without a related perspective in all statistical models. Hypothesis 2 was also supported by the results of models 1–4. The statistical comparison of the betas of *only related perspective* and *related & unrelated perspective* showed that being able to combine a related and an unrelated perspective led to significantly higher performance than only being able to take a related perspective. The economic impact analyses showed that these results are not only statistically significant but were quite substantial in terms of their expected financial compensation and changes of winning (both of ranked in the top 20 and of being the highest ranked contribution). In the following section we further discuss the theoretical and managerial implications of these findings.

5. Discussion

Crowdsourcing theory and practice have generally argued that organizations should make full use of the opportunities that digital technologies provide to focus on including individuals in their open innovation initiatives who are "distant" from the organization in terms of their knowledge background (e.g. Afuah and Tucci, 2012). In this study, we have shown that this might not be the best strategy; individuals who lack a related perspective are not well-positioned to contribute valuable ideas and suggestions to organizations' crowdsourcing initiatives. Indeed, our findings show that individuals who have a foot in both a related and an unrelated perspective are able to take insights from unrelated domains and integrate and recombine them with what they know from related domains are best positioned to contribute valuable ideas and suggestions to organizations' crowdsourcing initiatives (e.g. Dahlander et al., 2016). These findings have important implications for the literature on (inbound) open innovation and crowdsourcing in particular.

5.1. Theoretical implications and future directions

This study has several important implications for theory. First and foremost, our study shows that related and unrelated perspectives play independent and interdependent roles in the process of creative problem-solving tasks, such as idea generation, and that it is therefore important to theorize about domain knowledge and knowledge outside of the domain of the task as two distinct 'inputs' in the creative problem-solving process. While several studies on the use of external sources for innovation have considered individuals (or organizations) to have a certain knowledge distance from the organization engaging in the open innovation initiative (e.g. Acar and Van den Ende, 2016; Jeppesen and Lakhani, 2010; Katila and Ahuja, 2002), our study shows that this view of the knowledge background of external sources might be incomplete.

Indeed, the perspective offered in this paper – as an alternative to knowledge distance–puts prior research findings in a new light and may explain some of the findings more comprehensively. For example, in the science problem-solving contests that have been extensively studied (e.g. Acar and Van den Ende, 2016; Jeppesen and Lakhani, 2010), solvers actually *needed* to possess a domain-related perspective to even be able to make a contribution; something that is clear when you consider that "solvers were highly qualified; 65% of solvers reported holding Ph.D. degrees, and 19.1% advanced degrees" (Jeppesen and Lakhani, 2010, p. 1026). Thus, it is likely that the findings about the value of knowledge distance actually relate to the effects of having (a more well-developed) unrelated, marginal perspective *in combination with* contributors' domain-related perspectives. In other words, although conclusions of prior research have been different, research findings are actually very much in line with our proposed theorizing. Furthermore, in a study that considered idea generation tasks, Poetz and Schreier (2012) found that 'insiders' generated more useful and relevant ideas, while 'outsiders' came up with ideas that were more novel. Not only is our theory able to explain these findings comprehensively, but by thinking in terms of individuals being able to tap into related and unrelated perspectives, we can explain why in both groups some individuals were able to contribute ideas that were both useful and novel. Theorizing in terms of individuals being able to tap into multiple 'perspectives' instead of theorizing about having an 'optimal knowledge distance' to a problem domain thus allows researchers to better understand why some individuals will be able to transfer insights from unrelated fields to solve a particular problem, while most individuals in an unrelated field will not be able to do so.

To further advance our theorizing about related and unrelated perspectives as distinct drivers of creative problem-solving performance, it is important that future research investigate the factors that allow individuals ability to 'transfer' insights from one domain to another, and what factors might hinder this. This also relates to questions such as how large and complex do domain knowledge schemas need to be in order to integrate insights from unrelated domains and how the degree of dissimilarity between domains might affect how well individuals are able to integrate and recombine concepts. Finally, while we have focused on educational backgrounds, future research could take into account multiple perspectives that individuals might possess based on job experience, or other experiences that might provide relevant perspectives.

Second, our study has important implications for research on open innovation by highlighting the potential danger of "overreaching" when engaging in inbound open innovation initiatives, such as crowdsourcing for ideas and solutions. The results of our study clearly showed that a sole focus on individuals with different backgrounds and perspectives will actually lower the performance of an organization's crowdsourcing initiatives, by making it less likely that organizations obtain ideas that are novel and useful. This study contributes to future research on overreaching by investigating the educational background of individuals contributing to inbound open innovation initiatives. Our study provides future research on this important risk of open innovation with a clear focal construct to predict overreaching as well as a clear theory to determine other potentially important constructs in this respect.

Third, our study has implications for recent work in the field of open innovation that has investigated the importance of the characteristics of individuals *within* organizations engaging in inbound open innovation (e.g. Ahn et al., 2017; Bogers et al., 2018). While those studies have shown that it is important to understand the ability of individuals within organizations to absorb novel ideas and suggestions from outside of the organization, our study shows that it is also important that contributors are able to make their novel ideas absorbable by having an educational background that offers them related and unrelated perspectives. Besides showing the importance of individuals' personal characteristics for understanding organizations' ability to extract value from open innovation initiatives (e.g. Dahlander et al., 2016; Morgan et al., 2018; Schweisfurth and Raasch, 2018), our study also offers a potential policy implication with regard to the role of education and its impact on (open) innovation (e.g. Varsakelis, 2006): In the sense that multidisciplinary education enables individuals to take multiple perspectives and engage in cross-domain integration and recombination of concepts, more multidisciplinary educational training fosters individuals' abilities to become meaningful contributors to digital open innovation initiatives. Because it has become increasingly important to understand which skills will be needed to participate successfully in an increasingly digital society, our study makes a valuable contribution by implying that multidisciplinary educational training will help individuals be more successful in digital open innovation initiatives.

Fourth, our research has implications for research on innovation processes *within* organizations and the role individuals might play as contributors of ideas and suggestions. Although the argument in the crowdsourcing literature has generally been that employees are badly positioned to come up with novel insights, this ignores the fact that in most (larger) organizations there are usually a great number of different job functions and employees can represent a wide range of perspectives. What employees generally share though, is an understanding of what ideas might be useful and relevant for the organization (Bjelland and Wood, 2008). Given the importance of possessing a related perspective in generating valuable ideas for the organization, specifically targeting employees with unrelated perspectives within the organization might improve (internal) crowdsourcing initiatives (e.g. Malhotra et al., 2017; Zuchowski et al., 2016).

Fifth, because the risk of overreaching is exacerbated by the use of digital technologies for idea generation, future research could focus on the role digital technologies could play in idea selection (e.g. Hoornaert et al., 2017). Given that most idea selection mechanisms function poorly (Piezunka and Dahlander, 2015; Rietzschel et al., 2006, 2010), there is need for more research on the role digitization could play in idea selection (e.g. Alexy et al., 2012; Bjelland and Wood, 2008).

Finally, our results also showed that having done well previously positively affected both an individual's changes of participating again (see the Heckman selection models) and doing well again on crowdsourced idea generation tasks.[1] Even though, the general idea behind crowdsourcing is that anyone could contribute the next valuable idea for an organization (e.g. Afuah and Tucci, 2012; Bayus, 2013; Howe, 2008), our results indicate that some individuals were continuously more successful than others. Future research could investigate the factors that make some individuals able to continuously contribute valuable ideas to crowdsourcing challenges and the actions that digital crowdsourcing platforms can undertake to motivate these individuals to continue being a valuable contributor to their platform (see also Boons et al., 2015).

[1] We thank an anonymous reviewer for pointing us to this interesting result.

5.2. Managerial implications

This study also has important practical implications for organizations organizing crowdsourcing initiatives. The general sentiment of digital crowd-based platforms seems to have been to allow anyone to participate on any challenge, assuming that individuals will self-select to participate only on those challenges that they are best able to contribute valuable ideas to (e.g. Afuah and Tucci, 2012; Jeppesen and Lakhani, 2010; Mack and Landau, 2015). Unfortunately, in reality organizations still struggle to alleviate the combined problems of overreaching and crowding (e.g. Dahlander and Piezunka, 2015). Our study shows that is it important that digital crowd-based platforms further improve the efficiency and effectiveness of crowdsourcing initiatives by taking a more active approach to selecting potential contributors for specific innovation tasks. This would likely improve the ratio of (potentially) valuable ideas to noise and making it easier for organizations to absorb ideas obtained by crowdsourcing into the organization's innovation process (Piezunka and Dahlander, 2015), making the crowdsourcing process more efficient, in terms of overall costs and time spent, and effective in terms of leading to actual innovations (e.g. Alexy et al., 2012; Kornish and Ulrich, 2011). Crowdsourcing organizations could also explore how digital technologies can support organizations in idea selection, thereby alleviating the negative impact of overreaching and crowding (e.g. Hoornaert et al., 2017).

5.3. Strengths and limitations

All study designs have limitations and ours is no different. In this study, the outcome variables were both based on the ranking of individual ideas in the challenges by experts in the crowdsourcing organization. Because we were interested in the value of ideas *for the organization*, we considered the organization to be best positioned to decide on the performance of ideas. While this approach is in line with previous studies (e.g. Acar and Van den Ende, 2016; Jeppesen and Lakhani, 2012), a drawback of this approach is that it does not allow us to compare performances across challenges. While there are clear benefits to using the ranking of ideas based on the organization's evaluation of their overall value, future research could consider having individual contributions rated instead of ranked and not only on their overall value, but also on their novelty and usefulness to further investigate how individuals' backgrounds relate to the novelty and usefulness of their ideas and how these two aspects of ideas determine the overall value for organizations (see also Poetz and Schreier, 2012).

Secondly, we study educational background as a general proxy for individuals' perspectives in the context of a digital crowdsourcing platform for Dutch students and young professionals (up to 32 years old). Given our research context, using individuals' educational backgrounds seemed a reasonable, objective proxy for the perspectives of participants in these crowdsourcing challenges. However, since we were interested in relatively broad perspectives, we distinguished only between a 'Business and Economics' perspective, a 'Science and Technology', and 'Other'. Future research could allow for more fine-grained distinctions between and within perspectives to further explore the boundaries of 'perspectives' and how perspectives and other knowledge-related measures, such as level of expertise or knowledge depth, might affect performance on inbound open innovation initiatives. Being able to measure the degree of a person's expertise within a certain domain would also allow us to truly test how related and unrelated perspectives interact and moderate each other's impacts performance.[2]

Finally, individuals gain perspectives from many sources besides education throughout their lives and there are several digital crowdsourcing platforms that include participants from older, more experienced age cohorts and with a diversity of educational levels. While our data is a fair representation of most participants on digital platforms for innovation, who tend to be relatively young and highly educated, our study context was limited in that it focused on a specific subset of the total population and future research could investigate the role of other sources of perspectives in open innovation contexts with participants of more diverse backgrounds in terms of ages and nationalities.

6. Conclusion

In this study, we have argued that the relationship between the educational background of individuals and their performance in idea generation tasks on an online crowdsourcing platform is more nuanced than we would expect on the basis of existing crowdsourcing literature. Our results showed that having an educational background that allowed someone to take a related perspective positively affected the value of their ideas for the crowdsourcing organization. For individuals with a related perspective, being able to also tap into a perspective that was unrelated to the domain of the ideation task positively affected performance compared to only being able to make use of a related perspective. By theorizing in terms of related and unrelated 'perspectives' that have independent and interdependent effects on individuals' ability to generate creative ideas, this study advances our understanding of the mechanisms at the individual level that underlie successful inbound open innovation initiatives.

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[2] We thank an anonymous reviewer for the suggestion to consider the moderating effects of related and unrelated perspectives. Since individuals in our analyses always have either a related or an unrelated perspective, we cannot perform this analysis in our study and suggest this for future research.

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