Motivations and Solution Appropriateness in Crowdsourcing Challenges for Innovation

In press in Research Policy

Oguz A. Acar

Cass Business School (City, University of London)

(oguz.acar@city.ac.uk, +44 (0)20 7040 8592, 106 Bunhill Row London EC1Y 8TZ)

Motivations and Solution Appropriateness in Crowdsourcing Challenges for Innovation

Abstract

Crowdsourcing challenges are fast emerging as an effective tool for solving complex innovation problems. The main strength of the crowdsourcing model is that it brings together a large number of diverse people from all over the world to focus on solving a problem. This openness, however, results in a large number of solutions that are not appropriate, and this inhibits organizations from leveraging the value of crowdsourcing efficiently and effectively. It is therefore essential to identify ways to increase the appropriateness of solutions generated in a crowdsourcing challenge. This paper takes a step towards that by exploring what motivates the *crowd* to participate in these challenges and how these motivations relate to solution appropriateness. Drawing on data from InnoCentive, one of the largest crowdsourcing platforms for innovation problems, this paper shows that the various types of motivation driving crowd members to participate were related in different ways to the appropriateness of the solutions generated. In particular, intrinsic and extrinsic motivation were positively related to appropriateness whereas for learning and prosocial motivation the relationship was negative. The association between social motivation and appropriateness was not significant. The results have important implications for how to better design crowdsourcing challenges.

Keywords: motivation, solution appropriateness, open innovation, crowdsourcing, innovation contests, innovation tournaments

1. Introduction

Advances in digital technologies are fundamentally transforming the innovation practices of organizations. These technologies have blurred the boundaries of innovation processes and in turn have provided organizations with unprecedented opportunities in their search for innovation (Afuah and Tucci, 2012; Harhoff and Lakhani, 2016; Nambisan et al., 2017). Interested in leveraging the potential of digitization, organizations are increasingly using crowdsourcing challenges (i.e., open competitions in which crowd members compete to generate the best solution(s) in return for a financial prize) to tackle complex innovation problems. From breakthroughs in the discovery of new drugs to designing algorithms that can transform diagnosis of various diseases, these challenges have proved to be an effective way of harnessing the creative potential of the *crowd* to solve thorny problems (Acar and van den Ende, 2015; Lakhani et al., 2013; Saez-Rodriguez et al., 2016). The main value of the crowdsourcing model for innovation is that a large and diverse group of people are attracted to engage in problem-solving – not only experts from within the problem domain but also outsiders such as scientists from other domains or hobbyists who may have fresh ideas and perspectives to contribute (Acar and van den Ende, 2016; Boudreau et al., 2011; Jeppesen and Lakhani, 2010).

This scale and diversity, however, may inhibit organizations from harnessing the creative potential of the *crowd* effectively or may discourage them from using crowdsourcing altogether. The sheer volume of solutions generated in crowdsourcing can be overwhelming for many organizations (Blohm et al., 2013). Following the infamous Deepwater Horizon oil spill, for example, BP turned to the *crowd* for potential solutions on how to deal with the disaster, which led to 123,000 ideas being sent in from over 100 countries (Goldenberg, 2011). Likewise, the Netflix Prize, a crowdsourcing challenge for an algorithm to improve Netflix's existing

Cinematch algorithm by 10%, led to almost 45,000 submissions, and the winning submission alone contained over 100 individual algorithms (Netflix, 2017). This large volume of solutions submitted can be particularly problematic as they can vary greatly in terms of their appropriateness; many of the submissions are entirely unsuitable for various reasons, including not meeting the main technical requirements and goals specified in the challenge or containing limited and vague information (Blohm et al., 2013; Huang et al., 2014). Such solutions may be of limited or no value to the challenge organizer, but sorting through the submissions and evaluating them consumes substantial organizational resources and prevents the organizer from being able to implement solutions quickly. BP's crowdsourcing effort, for example, was described as "a lot of effort for little result" in an article about the incident in the *Guardian* newspaper (Goldenberg, 2011).

In addition to being very costly in terms of time and resources, receiving a large number of inappropriate solutions may make it hard for an organizer to successfully identify the solutions with the greatest potential. This is because organizations have a limited attention span (March and Simon, 1958; Ocasio, 1997), and the amount of attention they can devote to a decision will be dependent on what other decisions require their attention at that particular time (Cyert and March, 1963). Having to look at less worthwhile solutions therefore means that other more valuable solutions may not be getting the attention they deserve. In addition, having a large number solutions may also affect the way in which organizations filter solutions. For example, Piezunka and Dahlander (2014) found that when organizations face what they call *crowding* – i.e., receiving a large number of solutions in a crowdsourcing initiative – they tend to focus their attention on those that are already familiar to them (see also Criscuolo et al., 2017). This may inhibit them from making use of novel knowledge, one of the main reasons for organizing

crowdsourcing initiatives for innovation (Afuah and Tucci, 2012), and in turn prevent them from reaching potential breakthrough solutions to their innovation problems.

Crowdsourcing initiatives therefore often entail an inherent tension. On the one hand, organizations want to be completely open in their use of crowdsourcing so as to avoid missing any potentially promising solutions. On the other hand, this openness hinders organizations' ability to make efficient and effective use of the solutions they receive. In light of this tension, organizations would ideally want to have as few solutions as possible without excluding any that may have at least some chance of offering a breakthrough for the innovation problem. One way of navigating this conundrum successfully is to focus mainly on appropriate solutions – i.e., solutions that meet the specific constraints of a problem (Hennessey and Amabile, 2010; Mehta et al., 2012). The underlying logic is that appropriateness could be considered a necessary condition for a solution to be a potential breakthrough. That is, a solution which is not in line with the main constraints of a problem (e.g., solution requirements of a crowdsourcing challenge such as those relating to cost, performance or compatibility) is unlikely to stand a chance of being one of the best solutions, as it does not really solve the problem, no matter how novel it is. Such a solution is thus less worthy of inclusion in the set of possible solutions for consideration.

In sum, having fewer but more appropriate solutions is likely to enable organizations to better leverage the value of crowdsourcing by improving the effectiveness of the selection process, and making it swifter and more cost-effective. However, our understanding of what factors stimulate crowd members to generate submissions is still limited. In this paper, I aim to add to this understanding by exploring the motivational underpinnings of solution

appropriateness. That is, I examine what effects different types of motivation[1] may have on the appropriateness of solutions generated in a challenge. Understanding the nuances of this relationship is important for two main reasons. First, it is unlikely that all forms of motivations will have an identical impact on outcomes. Psychologists and management scholars have suggested and shown, for example, that different types of motivation (e.g., intrinsic and extrinsic) may trigger different motivational and cognitive processes and have different effects on innovation-related outcomes (e.g., Amabile, 1996; Ryan and Connell, 1989; Ryan and Deci, 2000). Hence, studying the link between motivation and appropriateness is a promising area of inquiry to understand the variance in solution appropriateness. Second, the motivation of participants could be influenced by how a challenge is designed. That is, by incorporating incentives that are likely to resonate with people with certain motives[2], challenge organizers could (i) encourage participation by *crowd* members who are likely to generate appropriate solutions and (ii) discourage those who are likely to generate inappropriate ones (e.g., Leimester et al., 2009; Sauermann and Cohen, 2010). A better understanding of the relationship between motivations and solution appropriateness could therefore enable organizers to have a solution pool which contains a manageable number of highly appropriate solutions.

Drawing on rich data from one of largest crowdsourcing platforms for innovation problems, InnoCentive, this paper addresses how different types of motivation relate to solution appropriateness. Specifically, I focus on five main motivations for participating in crowdsourcing challenges: intrinsic motivation (i.e., anticipation of deriving positive feelings

[1] Types of motivation refers to different reasons why individuals engage in an activity. Drawing on self-determination theory (Ryan and Deci, 2010), motivation types are viewed as a continuum ranging from intrinsic to extrinsic with different internalized motivations in between these two ends.

[2] Motivation is different from motives and incentives. Motives are trait-like preferences and incentives are benefits attached to doing a task (Sauermann and Cohen, 2010). Motivation, however, is a state-like psychological process that drives action in a specific task.

from engaging in creative problem-solving), learning motivation (i.e., desire to learn new things and improve one's skills), prosocial motivation (i.e., desire to make a positive impact and contribute to something that matters), social motivation (i.e., desire to feel part of a social unit), and extrinsic motivation (i.e., desire to win the prize or to acquire non-pecuniary benefits such as potential recognition and better career prospects). The results show that these motivations relate in different ways to the appropriateness of the solutions generated by the *crowd*. In particular, intrinsic and extrinsic motivations were associated with more appropriate solutions whereas learning and prosocial motivations were negatively related to solution appropriateness. Social motivation was not significantly associated with appropriateness.

These findings contribute to the crowdsourcing literature by taking the first steps to explore the motivational underpinnings of solution appropriateness. Despite the extensive research on motivations to participate in crowdsourcing (e.g., Boons et al., 2015; Hertel et al., 2003; Lakhani and Wolf, 2005; Mair et al., 2015; Roberts et al., 2006), it remains unclear how different motivations affect the appropriateness of solutions generated by the *crowd*. By exploring how these different motivations take effect, this research also contributes to the emerging research on how organizations can overcome the challenges inherent in crowdsourcing inititatives. While previous research has focused on the challenge of how to maintain the motivation of crowd members whose ideas are rejected (Piezunka and Dahlander, 2018) and how to encourage those within organizations to accept crowdsourced solutions (Lifshitz-Assaf, 2017), I am unaware of a study that has addressed the problem of receiving too many inappropriate solutions. From a practical standpoint, the insights generated in this study have implications for how organizations can better design crowdsourcing challenges so that they stimulate solutions

that are more appropriate and can in turn extract greater value from their crowdsourcing initiatives.

The remainder of the paper is organized as follows. Section two starts with an overview of the extant literature on crowdsourcing and motivation, and presents hypotheses. Section three details the methods of the study while section four reports the analysis and results. In section five, I discuss the findings of this study and conclude by highlighting the implications and limitations of the research, as well as areas for future study.

2. Theoretical Background

2.1. Crowdsourcing for Innovation

Crowdsourcing refers to the activity of opening up an organizational task to a large external *crowd,* typically via the Internet (Afuah and Tucci, 2012; Howe, 2006). Although the term crowdsourcing was coined relatively recently (by Jeff Howe in an article published in *Wired* magazine in 2006), using crowdsourcing for innovation purposes is not new (Majchrzak and Malhotra, 2013). The British Parliament, for example, organized an open contest, the Longitude Prize, in the eighteenth century and offered a £20,000 prize for an invention that could reliably determine longitude at sea – one of the greatest scientific problems of the day (Jeppesen and Lakhani, 2010). The Longitude Prize is just one of the many historical examples; from canned foods to fire extinguishers, many inventions have been developed following on from crowdsourcing challenges (Rosenberg, 2012). What is different in the digital age is that the potential of crowdsourcing challenges has grown remarkably, thanks to the Internet and the advance of communication technologies. That is, crowdsourcing initiatives bring unprecedented opportunities for organizations to tap into diverse ideas, knowledge and creative potential from all over the world. Prior research has indeed shown that crowdsourcing is of great value in

solving complex innovation problems (Acar and van den Ende, 2016; Jeppesen and Lakhani, 2010; Lakhani et al., 2013) and generating innovative ideas which can lead to development of products that outperform those generated by company designers in terms of important market performance metrics such as sales and gross margin (Nishikawa et al., 2013; Poetz and Schreier, 2012).

Crowdsourcing for innovation takes two main forms. The first one is *crowdsourcing communities* (and is sometimes referred to as collaboration-based crowdsourcing) in which members of the crowd interact and collaborate with each other to generate creative outcomes on an ongoing basis (Afuah and Tucci, 2012; Bayus, 2013; Schemmann et al., 2016). One well-known example is the Starbucks online community (MyStarbucksIdea.com) where the *crowd* share their ideas for new products and services (and other brand-related issues), and comment on each other's ideas (Acar and Puntoni, 2016). Crowdsourcing communities can take many shapes and forms in terms of the types of activities users undertake, ranging from the development of software codes (e.g., open-source software communities) to the generation of new product concepts (e.g., brand communities) (Afuah and Tucci, 2012; Lakhani and Wolf, 2005; Schau et al., 2009; Stahlbrost and Kareborn, 2011); the common denominator in these diverse communities is the collective generation of innovative outcomes.

The second form – the focus of this paper – is *crowdsourcing challenges* (also called innovation contests or tournament-based crowdsourcing) where members of the crowd compete with each other to generate the best outcome to an innovation problem (Afuah and Tucci, 2012; Boudreau et al., 2011; Saez-Rodriguez et al., 2016; Terwiesch and Xu, 2008). The historical examples provided above, and the Netflix example in the introduction, fall into this category. In contrast to crowdsourcing communities, where collective efforts and collaboration are the

underlying drivers of value, crowdsourcing challenges emphasize independent experimentation and competition (Boudreau and Lakhani, 2013)[3]. Crowdsourcing challenges are receiving growing interest from scholars, and research has already examined how the particular characteristics of the problems, the design of the challenge, the level of competition, and the expertise of *crowd* members can affect the solutions generated by the *crowd* (Acar and van den Ende, 2016; Afuah and Tucci, 2012; Boudreau et al., 2011; Garcia Martinez, 2015; Jeppesen and Lakhani, 2010).

However, research on the relationship between different types of motivations and the appropriateness of the solutions has been limited. This is an important limitation because such an understanding is likely to be valuable in terms of receiving an 'ideal' solution set (i.e., a manageable pool of appropriate solutions) to leverage the potential of crowdsourcing effectively and efficiently. This is because motivations are not only likely to explain differences in solution appropriateness but also are likely to be influenced by the presence and absence of incentives in a challenge (e.g., Leimester et al., 2009; Ryan and Connell, 1989; Sauermann and Cohen, 2010). A more nuanced understanding of the motivation-appropriateness link therefore facilitates designing platforms and challenges that can promote more appropriate solutions.

2.2. Motivations to Take Part in Crowdsourcing

Motivation is a psychological process that initiates action in a task and determines the form, duration and intensity of engagement in that task (Ambrose and Kulik, 1999; Grant, 2008). Psychology research has shown that people engage in activities for different reasons, and the distinction has often been made between intrinsic and extrinsic motivation. Intrinsic motivation

[3] It is worth noting that some crowdsourcing platforms may take a hybrid form, i.e., may entail challenges with collaborative elements.

refers to undertaking an activity for the spontaneous satisfaction derived from engaging in the activity itself, whereas extrinsic motivation refers to doing an activity because of external contingencies such as rewards and punishments (Ryan and Connell, 1989). This distinction, albeit useful, may not in fact be sufficient to capture the full range of reasons why individuals do what they do. That is, people may engage in an activity for reasons other than intrinsic or extrinsic motivation; they may do it, for example, because they set store by that activity.

Indeed, self-determination theory (SDT) of motivation posits that motivation is better viewed as a continuum, with intrinsic motivation at one end, extrinsic motivation at the other, and various forms of internalized extrinsic motivation, or more simply *internalized motivation*, in-between (Ryan and Connell, 1989; Ryan and Deci, 2000). Within the SDT framework, the distinction between intrinsic, internalized, and extrinsic motivations is based on their level of relative autonomy; that is, the motivations are categorized based on how free from external influence individuals feel when undertaking an activity (Gagné and Deci, 2005; Ryan and Deci, 2000). Individuals experience the greatest level of autonomy when they are intrinsically motivated, as their engagement is driven by the enjoyment they derive from the activity itself. In other words, intrinsically motivated people feel that their effort is completely voluntary. Internalized motivation involves less autonomy than intrinsic motivation; this is because here the effort is driven not by inherent interest in the activity per se, but by the belief that it will help in some way in achieving another self-selected goal to which the individual attaches particular value. The effort may therefore feel less voluntary; individuals would often need to push themselves to exert and sustain effort in the activity (e.g., Grant, 2008). Internalized motivation nevertheless involves more autonomy than extrinsic motivation, where the behavior is driven completely by an external contingency imposed by others. To put this differently, more

involvement of the 'self' in determining what goal to pursue (i.e., following one's own goal as opposed to an externally imposed contingency) makes internalized motivation a more autonomous form of motivation than extrinsic motivation.

SDT has often been a used as a main theoretical framework in studies exploring motivations in crowdsourcing communities (von Krogh et al., 2012). For example, scholars have established the importance of intrinsic and extrinsic motivations in open-source software (OSS) communities while also unearthing various forms of internalized motivations (e.g., own need for the software, willingness to improve programming skills, reciprocity expectations, social identification, altruism[4]) that drive members to generate and share their software codes (Hars and Ou, 2002; Hertel et al., 2003; Lakhani and Wolf, 2005; Roberts et al., 2006; Wu et al., 2007; see von Krogh et al., 2012 for a review). In a similar vein, motivations, such as gaining status and recognition, enjoying oneself, learning and improving one's skills, social identification, and winning an external outcome, were found to influence engagement in various other user and innovation communities (Füller et al., 2007; Jeppesen and Frederiksen, 2006; Lüthje, 2004; Nambisan and Baron, 2010, 2009; Stahlbrost and Kareborn, 2011).

In the context of crowdsourcing challenges, however, studies that address the diversity of motivations to take part in crowdsourcing challenges have been relatively scarce (Afuah and Tucci, 2012). Much of this research highlighted the importance of one specific type of extrinsic motivation (i.e., challenge prizes for winners) and focused on the optimal design of prizes to drive the crowd's effort and performance (e.g., Acar, 2018; Ales et al., 2017; Hofstetter et al.,

[4] Researchers have not always categorized these motivations as internalized motivation. However, according to the SDT framework, these motivations are internalized because engagement is driven by reaching a separable outcome, which is characterized by personal importance and conscious valuing. Put differently, these motivations are not described as intrinsic in the SDT framework, as the engagement is not driven by the inherent satisfaction of the activity itself.

2017; Terwiesch and Xu, 2008). Nevertheless, scholars have started to acknowledge that other reasons (i.e., intrinsic and internalized motivations) may explain why those in the crowd participate in challenges to solve complex innovation problems, above and beyond monetary prizes (Boons et al., 2015; Frey et al., 2011; Lakhani et al., 2007; Leimester et al., 2009; Murray et al., 2012). Murray and colleagues (2012) have, for example, identified having fun, reputation and publicity, and environmental concerns as the most important reasons why people participated in the Progressive Automotive Insurance X PRIZE challenge. Leimester et al. (2009) have suggested that learning is also an important motivation for the crowd, whereas Boons, Stam, and Barkema (2015) have shown that social motivations (i.e., feelings of pride) are a significant driver of members' activity levels in a crowdsourcing platform. Lakhani et al. (2007) have added to this understanding by not only identifying a set of important motivators of the crowd but also documenting the motivational differences between winning and non-winning solvers.

Overall, prior research has shown that participation in crowdsourcing communities and challenges are driven by diverse motivations, which can be categorized under intrinsic, internalized, and extrinsic within the SDT framework (e.g., Fuller, 2010; Roberts et al., 2006; von Krogh et al., 2012)[5]. Researchers have also taken important steps to document how different

[5]Although the literature review indicates that motivations for engagement in crowdsourcing communities and challenges overlap to a great extent, there may be subtle differences between the two. One important systematic difference, which is likely to have consequences for motivation, is that communities and challenges differ in terms of their predominant mode of creation (i.e., whether innovation relies mainly on competition or on collaboration between crowd members). Indeed, psychology and behavioral neuroscience research has shown that competition (as opposed to collaboration) brings about motivational differences (e.g., Carr and Walton, 2014; Deci, Betley, Kahle, Abrams, and Porac, 1981; Le Bouc and Pessiglione, 2013). Likewise, Boudreau and Lakhani (2013) point to potential motivational differences between collaborative and competitive crowdsourcing platforms. The literature review suggests that reciprocity-based motivation, a form of motivation widely discussed in relation to participation in crowdsourcing communities, is not included as a driver of participation in challenges. This could be explained by differences in the predominant mode of creation, given the research documenting associations between reciprocity-based motivation and preference for social cooperation (see Fehr and Gintis, 2007, for a review). In light of this, reciprocity-based motivation is not included in my theoretical model.

motivations relate to members' level of effort, contributions, and activity in such platforms (e.g., Boons et al., 2015; Hertel et al., 2003; Lakhani and Wolf, 2005; Mair et al., 2015; Nambisan and Baron, 2009; Roberts et al., 2006). However, studies linking these different types of motivations to the appropriateness of the outcomes generated in crowdsourcing have been limited. Basing on a review of the OSS literature, von Krogh et al. (2012) have, for example, concluded that "while research on motivation in OSS generated a clear link between extrinsic and intrinsic motives and contributions, it did not relate individual motivation to the quality of the contributions made" (p. 655). This observation has been echoed by Malinen (2015) in her systematic review of research on user participation in online communities.

2.3. Motivations and Solution Appropriateness in Crowdsourcing Challenges

In line with SDT and prior research on motivation and innovation (Sauermann and Cohen, 2010), I expect different types of motivation to impact in different ways on the activities that individuals undertake when they are searching for a solution to an innovation problem – activities which may then affect appropriateness of the solutions they generate. Scholars have often conceptualized appropriateness as an essential dimension of creative outcomes.[6] It concerns the production of solutions that are *fitting* to the problem at hand – i.e., that meet the specific constraints in a situation – and hence potentially of value in resolving it (e.g., Hennessey and Amabile, 2010; Runco, 2004; Runco and Charles, 1993; see also Mehta et al., 2012; Yang et al., 2012). This conceptualization suggests that appropriateness of a solution is determined according to the bounds of a specific context (i.e., what is appropriate in one context may not be

[6]Prior research established that creativity has two main dimensions: appropriateness and novelty (originality) (e.g., Amabile, 1996; Runco, 2004). Like appropriateness, novelty is considered to be contextual and refers to the extent to which an idea is unique compared to other ideas available within a context (e.g., Shalley et al., 2004). Recent research have documented that these two dimensions are distinct and are motivated by different and, sometimes, opposite conditions (e.g., Bechtoldt et al., 2010; Miron-Spektor and Beenen, 2015).

appropriate in another) (Miron-Spektor and Beenen, 2015; Perry-Smith and Shalley, 2003). In the context of crowdsourcing challenges, a submission is deemed appropriate when it contains a solution within the constraints of a challenge (e.g., technical requirements, performance goals). As such, motivations are expected to increase the appropriateness of solutions when they make those working on solutions focus more attention and effort on meeting the specified goals and requirements of the challenge.

I focus on intrinsic and extrinsic motivation, and three different types of internalized motivations: learning motivation, social motivation and prosocial motivation[7]. Intrinsic motivation is often considered to be the primary motivational driver of engagement and performance in creative activities (Amabile, 1996; Hennessey and Amabile, 2010). The *crowd* members are likely to pay considerable attention to the problem constraints (e.g., requirements, objectives) when they are intrinsically motivated as the problem itself is the main driver of engagement. In other words, those constraints are an essential part of the problem and thus are important for intrinsically motivated people. Also, to derive positive feelings from solving a challenging problem successfully one needs a good understanding of what makes a successful solution. In addition to focusing more on what is required in a solution, intrinsically motivated people are better suited to generating solutions that can meet problem specifications. Solutions to crowdsourcing challenges are often not obvious; finding one that can meet the problem constraints is therefore not straightforward (Acar and van den Ende, 2016). *Crowd* members with higher intrinsic motivation are more likely to persist in searching for a way to meet these

[7]The motivation categories were determined based on the SDT and my review of motivation research on crowdsourcing. Arriving at these categories involved three steps. First, I identified each type of motivation that had been studied in previous research on crowdsourcing challenges and communities. Then I excluded any types of motivation that were relevant to crowdsourcing communities but not to challenges (e.g., reciprocity-based motivation). Finally, I iteratively compared each type of motivation according to the level of self-determination involved, and clustered them based on the SDT framework (i.e., intrinsic, internalized and extrinsic motivation).

constraints when they encounter difficulties (e.g., Ryan and Deci, 2000; Shalley et al., 2004), and hence are more likely to generate appropriate solutions:

Hypothesis 1: Intrinsic motivation is positively related to solution appropriateness in crowdsourcing challenges.

Individuals with a high learning motivation are focused on acquiring new knowledge and developing new skills (Barron and Harackiewicz, 2001; Brett and VandeWalle, 1999). They will often tend to view the problem presented in the challenge as an opportunity to explore new knowledge domains or new territories within a knowledge domain. Such a motivational orientation is likely to lead to considerable attention being given to acquiring new skills and knowledge, because active learning is a difficult and demanding process (Bell and Kozlowski, 2008; Simons and De Jong, 1992). As the cognitive effort required to deal with novel information is substantial (Acar and van den Ende, 2016; Li et al., 2013), those who are dealing with new material are likely to have little if any capacity left to focus also on generating appropriate solutions – i.e., satisfying specific problem constraints. It is worth noting that a learning motivation may facilitate the acquisition of knowledge and skills (Brett and VandeWalle, 1999) which may help the individual to develop more appropriate solutions in subsequent challenges (Gardner, 1993; Hayes, 1989). However, when the actual learning takes place while an individual is generating a solution to a specific challenge, the appropriateness of solution in that particular challenge is likely to be compromised.

Hypothesis 2: Learning motivation is negatively related to solution appropriateness in crowdsourcing challenges.

When prosocially motivated, individuals are focused on doing things that will have a positive impact on others (Grant, 2008) and are driven to generate ideas that are useful to others

(Grant and Berry, 2011; Liu et al., 2016). The problems in a crowdsourcing challenge serve as an opportunity for them to make a meaningful contribution to the challenge organizer. This form of motivation prompts people to consider others' needs and thus likely to direct their attention to understand what the problem is. In other words, prosocially motivated *crowd* members are likely to spend time trying to understand what organizers really require in a specific challenge. Moreover, they are well suited to come up with a solution that will be most helpful to the challenge organizers because prosocial motivation stimulates people to put themselves in others' shoes when generating a solution (Grant and Berry, 2011). Taken together, a greater emphasis on the needs of organizers and willingness to take their perspectives is likely to promote generation of solutions that are fitting to their specific problem and hence yield more appropriate solutions.

Hypothesis 3: Prosocial motivation is positively related to solution appropriateness in crowdsourcing challenges.

Social motivations often arise from individuals' willingness to satisfy their need for belonging, as well as the value and significance they attach to group membership (Ashforth and Mael, 1989; Tajfel, 1978). One form of such a motivation, which has received substantial scholarly interest in prior crowdsourcing research, is social identification (e.g., Bagozzi and Dholakia, 2006; Boons et al., 2015; Hars and Ou, 2002; Hertel et al., 2003; Lakhani and Wolf, 2005; Nambisan and Baron, 2010). Social identification refers to a feeling of "oneness" with a social group, such as an organization or community (Ashforth and Mael, 1989). In crowdsourcing challenges, it concerns identification with a platform where challenges are posted. Researchers have shown that members are more willing to engage in behaviors that can support the goals of the organization they are identified with (Dukerich et al., 2002; Riketta, 2005). As one of the main goals of a crowdsourcing platform is to generate (potentially) valuable

solutions to innovation problems, which at the least requires ideas that can solve problems within their constraints, strongly identified members are likely to be willing to generate more appropriate solutions. Members' identification is also found to be positively related to participation in online communities (Dholakia et al., 2004; Nambisan and Baron, 2009), indicating that members are willing to expend greater effort once they are identified with a platform. Taken together, crowd members with high identification are likely to generate more appropriate solutions, as they are not only motivated to generate solutions that satisfies problem constraints but are also willing to invest necessary efforts to accomplish this.

Hypothesis 4: Social motivation is positively related to solution appropriateness in crowdsourcing challenges.

When extrinsically motivated, individuals engage in an activity to attain an external outcome (Ryan and Deci, 2000). These outcomes can take various forms; in the context of crowdsourcing challenges, they may be either winning the prize or boosting one's reputation or career. In order to achieve this, *crowd* members need to come up with a winning solution, which, by definition, means addressing the main constraints set out in the challenge. Extrinsic motivation therefore directs their attention and efforts towards generating a solution that is fitting for the problem at hand – i.e., more appropriate. This argument is in line with the established views in psychology and economics literature which suggests that external rewards (both financial and non-financial) will direct attention and effort towards activities for which rewards are being given (Eisenberger and Rhoades, 2001; Prendergast, 1999; Rynes et al., 2005). In sum, because reaching the external benefits that motivate the *crowd* is contingent on winning, extrinsically motivated *crowd* members are likely to focus their attention and effort on

generating a solution that satisfies the particular constraints of the problem and thus to produce more appropriate solutions.

Hypothesis 5: Extrinsic motivation is positively related to solution appropriateness in crowdsourcing challenges.

3. Methods

3.1. Research Setting

The context for this study is the InnoCentive platform. InnoCentive acts as an intermediary between its clients (who share their innovation problems with the company) and its community – over 380,000 *crowd* members from all over the world. InnoCentive has posted over 2,000 real-world innovation problems from clients including Toyota, Procter & Gamble, NASA and many others. These problems are posted on the InnoCentive online platform in the form of a contest, and interested members of the *crowd* submit their proposals as a written report. The client then evaluates the submitted solutions, decides on the winning solution, and awards a financial prize (typically ranging from 10,000 to 100,000 USD) to the winner. The InnoCentive platform presents real-world problems from various disciplines within life sciences, physical sciences and applied sciences. Overall, InnoCentive represents an appropriate platform for studying the role of motivations in crowdsourcing challenges, given that the platform is host to a wide range of innovation problems and diverse members from all over the world.

3.2 Sample, Procedures and Data

A web survey was conducted with those who had contributed solutions to the challenges on the InnoCentive platform. The sample included all members who had made at least a submission to a scientific challenge posted on the InnoCentive platform in the 2.5 years before the data collection

(i.e., between December 2009 and May 2012). More specifically, all solvers who submitted a solution to "Reduction-to-Practice" (RTP) and "Theoretical" challenges within this time span were included in the sample (N = 3,005). Theoretical challenges require participants to provide a detailed description of their solution, including specifications and supporting precedents. An example is designing a new, low-cost storage tank to harvest rainwater for use in a wetland region. RTP challenges require participants to provide not only a detailed description of their solution but also physical proof that it will work. An example is development of a contractible polymer system that can be applied directly to the skin. Both types of challenges include a description which details solution requirements. These requirements often relate to efficiency, performance and compatibility (e.g., a chemical that costs less than a specified amount while achieving particular purity levels and compatibility with certain RNA molecules; or an algorithm that can operate on certain file types while reaching a desired level of accuracy within a determined time span).

Using contact information retrieved from InnoCentive, a customized email with a URL link to the survey was sent to 3,005 solvers. The email asked for information relating to one specific challenge – the last one for which the respondent had submitted a solution. A reminder was sent a week later using a dynamic strategy (i.e., design features between the initial contact and the reminder were varied) to enhance the response rate (Sauermann and Roach, 2013). We received 744 (24.8 %) responses. Of those, 646 (21.5%) were usable for the analysis (i.e., had answers relating to one or more constructs of our study) (568 males, 56 females, with 22 unreported gender). The average age of participants was 44.21. Most of the respondents had a higher education degree (209 PhD, 158 Master's degree, 147 Bachelor's degree, 22 unreported). Participants were from different backgrounds, ranging from experts (academics, consultants) to

students, and from at least 66 different countries (the largest group being from USA with 260 respondents, 28 unreported). To assess whether non-response bias is an issue in our sample, we compared the responses of early respondents (i.e., the first third of respondents) and late respondents (i.e., the last third of respondents) using independent sample *t*-tests for each variable measured in this study[8]. The assumption in this analysis is that late respondents are closer to the non-responding group than early respondents (Rogelberg and Stanton, 2007). There were no significant differences in any of the variables measured for early and late respondents. Hence, although it cannot be ruled out completely with the data I have, I do not expect non-response bias to be a major concern for the study. The survey data was complemented with data from company archives on challenge characterics and solution appropriateness (exact details of data that is extracted from company archives are provided in Measures section).

3.3. Measures

3.3.1 Scale Development

The scales for our motivation constructs were developed based on qualitative research, prior motivation and online communities literature (Amabile et al., 1994; Grant and Sumanth, 2009; Guay et al., 2000; Roberts et al., 2006; Ryan and Connell, 1989; Ryan and Deci, 2000; Smidts et al., 2001), and a series of exploratory and confirmatory analyses.

The main purpose of this qualitative phase was to substantiate my understanding of the setting and inform the design of the survey. In particular, it helped in adapting our survey items from prior research for InnoCentive. In total, I conducted 10 semi-structured in-depth interviews with solvers. Following the recommendations of Eisenhardt and Graebner (2007) to incorporate

[8] The conclusion remained similar when early and late respondents were defined differently (i.e., when the first/last 10% or half is considered as early/late respondents).

diverse views on the questions of interest, I interviewed people in the InnoCentive community who had had different levels of success (i.e., multiple winners, single winners and non-winners). In the interviews, I asked respondents to discuss their reasons for participating in InnoCentive challenges and for solving scientific problems in general, and if they have not mentioned already, I whether the other motivations identified in the hypotheses section might also play a role in participation. In addition, I examined content from more than 80 individual solvers on the InnoCentive blog (358 posts), in forums (77 posts) and in LinkedIn (193 posts) groups regarding these motivation types.

In the survey, a seven-point scale was used for participants to indicate why they have participated to the latest crowdsourcing challenge they have taken part. A total of 28 different motivation items were identified from the qualitative study and prior research (see Appendix A). Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) techniques were used to identify and validate underlying dimensions of the motivations. In line with prior research (e.g., Wrzesniewski et al., 2014), I randomly split the sample, and conducted EFA with the first subset (N = 328) and used the other subset for CFA (N = 318) based on respondents' answers to questions on motivation. In the EFA, an oblique rotation technique (oblimin) was used to allow different types of motivation to correlate. The analysis revealed five factors that had eigenvalues greater than 1 (eigenvalues = 7.70; 2.86; 2.54; 1.28; 1.15). Items that loaded on at least 0.50 for one factor and did not load 0.30 or above on more than one factor were retained. In addition, one item was deleted due to face validity concerns (overall, 21 items were retained; see Appendix B) The final five-factor structure model explained 73.90% of the variance. The factors reflected *intrinsic motivation* (i.e., included items relating to fun and enjoyment derived from the process of problem-solving), *learning motivation* (i.e., included items relating to the motivation to

improve one's skills and learn new things), *prosocial motivation* (i.e., included items relating to the motivation to make a positive impact on others and contribute to something that matters), *social motivation* (i.e., included items relating to social identification) and *extrinsic motivation* (i.e., included items relating to the motivation to achieve external rewards such as career benefits, recognition or money). Next, I conducted a CFA with the other subset of the data. The results indicated, as expected, that the five-factor model provided an adequate fit with the data ($\chi 2 = 415.487$, root mean square error of approximation = 0.075, standardized root mean square residual = 0.053, comparative fit index = 0.938, Tucker–Lewis index = 0.927). In addition, chi-square difference tests indicated that this model provided a significantly better fit than alternative nested models.

3.3.2 Independent Variables

All motivation constructs are state-measures. They were measured with seven-point scales ranging from 1 "does not correspond at all" to 7 "corresponds exactly" unless indicated otherwise. The scale for intrinsic motivation included four items: "Enjoyment of creating new things", "Enjoyment of solving problems", "Feelings of being intellectually challenged", and "Feelings of satisfaction from being able to solve a problem" ($\alpha = 0.85$). The scale for prosocial motivation had three items: "Opportunity to work on something that matters", "Opportunity to work on 'real-life' problems", "Opportunity to benefit others through my solution" ($\alpha = 0.88$). Learning motivation was measured with four items, including "Learning new things", "Enhancing my skills", "Sharpening my brain", "Being updated with science", ($\alpha = 0.94$). Social motivation scale included five items: "I feel strong ties with InnoCentive", "I experience a strong sense of belonging to InnoCentive", "I feel proud to work for InnoCentive", "I am sufficiently acknowledged in InnoCentive", "I am glad to be a member of InnoCentive" $\alpha = 0.90$)

(1=strongly disagree, 7= strongly agree). Finally, the extrinsic motivation scale included five items: “Enhancing my career/business prospects”, “Recognition I will receive after solving the problem”, “Showing my competencies”, “Award money”, “Potential future income from the seeker” ($\alpha = 0.85$).

3.3.3 Dependent Variable

The measure for the dependent variable, solution appropriateness, was extracted from company archives; I utilized an internal scale used by InnoCentive to rate each solution. This system is designed to assess the appropriateness of solutions and serves two main purposes: filtering out the inappropriate solutions (so that these are not sent to clients) and providing clients with an initial indicator for each solution. It is worth noting that the rating is only shared with clients; crowd members are not informed of the rating for their solutions. Specifically, in this system, solutions are rated on a scale from 1 to 5. Submissions that have nothing to do with the challenge (e.g., completely off-topic, not even remotely address any of the requirements, extremely illegible or short) are rated 1 (and are not sent to clients); those that include an idea related to the challenge but do not address most of the requirements are rated 2; those that address most of the challenge criteria (but not all) are rated 3; those that address all the criteria are rated 4; and, finally, those that address all the criteria elaborately are rated 5. A higher rating therefore indicates that a submission is more effective in addressing challenge requirements. This measure is considered to be a suitable indicator of appropriateness in my context because challenge requirements in crowdsourcing describe the boundaries of an appropriate solution. As such, a submission is considered appropriate only if it presents a solution within the problem constraints. That is, problem constraints serve as the main reference point that determines how suitable a

solution is; the extent to which a solution is effective in addressing constraints determines its appropriateness level.

3.3.4 Control Variables

With regard to control variables, I collected data from company archives on challenge characteristics to account for the differences between the various challenges. Specifically, the size of the prize offered (log-transformed due to high skewness), type of challenge (i.e., "Theoretical" or "Reduction-to-Practice"), number of submissions made to a challenge, and duration of the challenge (i.e., how long the challenge remained open) were included as covariates in the analyses.

In addition to challenge characteristics, several individual factors may have influenced the results. Something that could potentially bias our analyses is that some of the respondents answered the questions about their motivations after they knew about the outcome, which may have influenced how they think about their motivations. To address this issue, I created a dummy variable (labeled *outcome awareness*) coded as 0 for challenges that were still open or under evaluation (i.e., challenges in which solvers were unaware of the final result) at the time of the survey and coded as 1 for challenges that had already been evaluated and the results communicated to solvers. This dummy variable was included as a control in the regression analyses. On a related note, people who have submitted solutions to challenges very recently may be more able to remember their motivations or may interpret their motivations differently to those who made submissions a long time ago. In particular, over time, the intensity of motivational states may be subject to change through processes of story-telling and identity construction (e.g., McLean et al., 2007). Thus, a respondent who participated a long time ago may be reporting on constructed motivational notions, and this may differ from a more recent

participant who may report more accurately on remembered motivational attitudes. To address this potential problem, I calculated a variable called *recency* that measures the total number of days passed between the date the Web survey was sent out (i.e., 16 May 2012) and the date the challenge was posted on the InnoCentive platform, and I included this as a control variable in the regression analyses.

In addition, our in-depth interviews suggested that constructs relating to prior knowledge can influence the level of motivation and engagement. Therefore, to account for the possibility that observed effects may be in part attributable to knowledge-related variables, I controlled for *knowledge distance* (i.e., the extent to which a discipline falls into one's area of expertise) and *education level*. Knowledge distance was measured with a seven-point scale where 1 indicated "inside my field of expertise" and 7 indicated "outside my field of expertise" (Acar and van den Ende, 2016; Jeppesen and Lakhani, 2010). Education level was assessed by asking respondents to indicate their highest level of academic achievement (six levels ranging from "less than a high school degree" to "PhD"). Dummy variables were created for each education level and the lowest level was used as the reference category.[9] Data for these two variables were collected via the web survey.

4. Results

Means, standard deviations and correlations are reported in Table 1. I started testing the hypotheses using hierarchical ordinary least squares (OLS) regression analyses. I entered all control variables in the first step, and motivation variables in the second step. The dependent

[9] For the analyses, the lowest two education levels – i.e., 'less than a high school degree' with 'high school degree or equivalent' – were merged to form a new category (highschool degree or less) because the former had too few responses (N = 8) to conduct a meaningful analysis. This new category had a total of 49 responses and served as the reference category in the analyses.

variable, solution appropriateness, was close to normal, with small skewness and kurtosis values (<1). Unsurprisingly, there were more inappropriate solutions than highly appropriate ones. Analyses of the residuals suggested that no serious violation of normality or homoskedasticity exists. In addition, a Durbin-Watson (DW) test provided support for the independence of error terms, as the DW statistics ranged from 1.86 to 1.97. As can be seen from Table 1, the motivation measures were highly correlated in line with prior research (Ryan and Connell, 1989). I therefore checked the variance inflation factors for all independent and control variables to determine whether substantial correlations between motivation constructs are problematic for the analyses. The highest variance inflation factor was 2.80 (well below the conventional cut-off of 10) (Hair et al., 1998), suggesting that multicollinearity was not a problem for the analyses.

--- Insert Table 1 about here ---

The results of the regression analyses are reported in Table 2, and show that these five motivations relate in different ways to solution appropriateness. As predicted in Hypothesis 1, intrinsic motivation was positively related to solution appropriateness ($\beta = 0.133$, $p = 0.016$). Hypothesis 2 was also supported; learning motivation was associated with a poorer appropriateness of solution ($\beta = -0.173$, $p = 0.003$). Contrary to Hypothesis 3, prosocial motivation was negatively related to solution appropriateness ($\beta = -0.111$, $p = 0.037$). Hypothesis 4 was not supported as well; social motivation was not significantly related to solution appropriateness ($\beta = -0.13$, $p > 0.25$). Finally, in line with Hypothesis 5, extrinsic motivations were associated with a greater appropriateness of solutions ($\beta = 0.115$, $p = 0.008$).

--- Insert Table 2 about here ---

5. Discussion and Conclusion

Crowdsourcing has emerged as a promising form of digital innovation; instead of relying on designated agents, more and more organizations are opening up their problem to *crowds,* typically via a digital platform (Afuah and Tucci, 2012). Despite the convincing evidence that crowdsourcing can be effective in solving complex innovation problems (e.g., Jeppesen and Lakhani, 2010; Lakhani et al., 2013), managing contributions from a large and diverse *crowd* presents significant challenges. In this paper, I examine how organizations can address one of the greatest challenges associated with crowdsourcing – dealing with large number of inappropriate ideas (Blohm et al., 2013; Huang et al., 2014). In particular, this study focuses on what effects *crowd* members' motivations have in terms of the appropriateness of the solutions they generate. By examining data collected from InnoCentive, where solutions are regularly evaluated based on their appropriateness, this paper demonstrates that not all motivations are created equal; while some forms of motivation seem to increase the level of appropriateness (i.e., intrinsic and extrinsic), others either reduce it (i.e., learning and prosocial motivation) or have no effect on it (i.e., social motivation).

There are at least three reasons why addressing the novel question of how crowd members' motivation affects solution appropriateness is essential in order to harness the potential of crowdsourcing more effectively. First, solution appropriateness is vital for realizing the main promise of crowdsourcing: utilizing distant knowledge for innovation (Afuah and Tucci, 2012). Appropriateness is not only a necessary condition for a breakthrough solution (i.e., a breakthrough solution needs to meet the constraints of a problem), but is also essential to an organization's ability to identify which solutions offer the greatest potential. This is because solution appropriateness affects how the submissions received are handled; receiving too many

inappropriate ideas narrows organizations' attention span, making them focus on familiar solutions rather than novel ones (Criscuolo et al., 2017; Piezunka and Dahlander, 2014). In other words, the organizations' evaluation processes become biased (against novelty) and can potentially lead to the selection of suboptimal winning solutions. Second, solution appropriateness is an important determinant of a crowdsourcing initiative's cost-effectiveness; inappropriate solutions take up too much of the organization's limited attention, which would be better directed towards more promising solutions. In other words, inappropriate solutions increase the costs of an initiative, as sorting through them and evaluating them consumes considerable organizational resource, without contributing to the value generated from the crowdsourcing. Third, the time required to evaluate inappropriate solutions causes unnecessary delays in implementing the winning solution(s). It therefore reduces the speed of new product development – a key performance outcome for innovation projects and one which is becoming increasingly important in today's rapidly shifting environment (e.g., Chen et al., 2010). Organizations are thus likely to derive greater value from crowdsourcing not by encouraging *more* solutions but by encouraging those which are appropriate and proactively *discouraging* those which are not.

As a whole, this study helps to provide a greater understanding of crowdsourcing challenges and contributes to the digital innovation literature. It does so by taking the first steps to explore the relationship between motivations and solution appropriateness. Although previous research has addressed motivations for participating in crowdsourcing initiatives, the effects of different motivations on the appropriateness of outcomes generated by the *crowd* remained unexplored. As dealing with a large number of solutions is often considered to be one of the greatest challenges in crowdsourcing, the findings of this study also contribute to the emergent

line of research on how organizations can overcome challenges involved in using crowdsourcing for innovation (Lifshitz-Assaf, 2017; Piezunka and Dahlander, 2018). Importantly, this study has implications for the broader literature on digital innovation as it addresses one of the key questions raised: how can organizations manage their innovation processes effectively when partnering with diverse and unspecified agents? (Nambisan et al., 2017). More specifically, this study provides useful insights into how to motivate such partners to provide inputs that are in line with organizational needs and requirements.

What could organizers of crowdsourcing challenges do to promote appropriateness in the solutions they receive? The first implication of this study is that they should use various extrinsic rewards in their crowdsourcing initiatives. In terms of what types of reward to include, I would encourage organizers to look beyond financial ones. The findings show that other non-pecuniary extrinsic benefits, such as recognition and career advancement, are also important drivers of appropriateness. Organizers could, for example, simply feature winning solutions/solvers (as well as a few other close contenders) not only on the platform itself but also in their company blogs, social media pages and many other media outlets whenever possible. When working out what form of publicity and recognition might be most effective, organizations could look at the practices of online platforms elsewhere for inspiration, as a wide range of practices are being used successfully to encourage the generation of content that will be more useful to the platform. Practices used to acknowledge and publicize top performers include leaderboards (i.e., league tables of the most successful *crowd* members), status badges that members can include in their profiles and performance statistics for individual members (Dellarocas, 2010). In addition to incorporating extrinsic benefits into challenges, organizers should also promote the intrinsic benefits of participation. In the light of prior research that highlights the importance of perceived

autonomy and competence for intrinsic motivation (e.g., Hennessey and Amabile, 2010; Ryan and Deci, 2000), organizers of crowdsourcing initiatives could seek to eliminate any potentially constraining elements of the problem or the platform that might reduce participants' sense of autonomy and they could provide positive verbal or written feedback that might enhance participants' feelings of competence.

At the same time, challenge organizers should consider downplaying the learning opportunities offered by crowdsourcing challenges as well as the prosocial aspects. Both learning and prosocial motivation, despite being important reasons for participation, are associated with generating inappropriate solutions. Although organizers of crowdsourcing challenges may not be able to filter out those with a high learning or prosocial orientation entirely, given that participation is open and voluntary, they could take steps to avoid encouraging such participants. For example, because providing learning opportunities (e.g., experts, mentors, or resources) is likely to attract those with a high learning motive (Leimester et al., 2009), organizers should refrain from incorporating these in crowdsourcing challenges and inititatives. However, it is worth noting that learning motivation might have a positive impact on performance in the long run, as found in recent research, because using one's acquired knowledge to solve problems may require time (Gong et al., 2009). When crowdsourcing challenges are posted frequently, it might therefore still be useful to encourage individuals with a high level of learning motivation to take part, as they may then use what they have learnt to develop more appropriate solutions in subsequent challenges. With regard to prosocial motivation, it is important to avoid mentioning potential other-related benefits (i.e., how solving this problem will help others) in challenge descriptions. Organizers could also avoid providing information about those who may be helped in some way by solutions generated, or putting crowd members in touch with these beneficiaries,

as that may strengthen crowd members' willingness to make a prosocial impact (Grant, 2007, 2012). Finally, because social motivation is neither detrimental nor beneficial to solution appropriateness, organizers might do better to channel their resources into developing stronger extrinsic and intrinsic incentives rather than improving crowd members' sense of social identification.

Two of the unexpected findings merit further discussion and future research efforts. First, in contrast to my hypotheses, the results show that prosocial motivation is negatively related to the appropriateness of solutions. One explanation for this finding may be found in prior research which suggests that prosocial motivation can be driven by different personal goals, ranging from wanting to help others because they genuinely care about them to wanting to do so because it will make them feel better about themselves (Batson and Shaw, 1991; Grant and Berry, 2011). It could be that most of the prosocially motivated people in our context are driven by the second of those goals, namely feeling good about themselves, rather than by a genuine concern for others' problems. If this is the case, those *crowd* members might be satisfied by simply providing their standpoint on the problem, and leaving it to the challenge organizer to decide what to do with it; they may not really be concerned about developing a more appropriate solution that can meet all the requirements of that particular challenge. It is also worth noting that in our context, companies setting the challenge is typically not known to the *crowd* members, which may make it more difficult for crowd members to look at things from their perspective. Given that perspective taking has been found to be the main mechanism through which prosocial motivation leads to the generation of useful ideas (Grant and Berry, 2011), *crowd* members may fail to come up with a solution that can solve the challenge organizers problems. Another plausible explanation for this finding could be that prosocially motivated people prioritize solving a

problem in a way that can help as many beneficiaries as possible rather than making their solutions fit with problem constraints. Put differently, crowd members who are more prosocially motivated may not be willing to limit their search processes when they think problem constraints do not help with contributing to a sizeable number of potential beneficiaries.

The second finding that contrasts my hypotheses is that social identification with a crowdsourcing platform is not significantly related to solution appropriateness. One potential reason for this could be that crowd members may not perceive that their solutions contribute to the platform, as the challenges in our context are often the problems of external organizations. That is, crowd members may fail to foresee the potential future benefits of their solutions for the platform (e.g., in terms of reputation and/or future businesses) and thus may not focus their attention and effort on generating appropriate solutions. This suggests that identification may drive appropriateness when crowd members realize the value of their solution for the platform (e.g., when the challenges posted are the platform's own problems or when the benefits of the appropriate solutions for the platform are communicated clearly). Importantly, social identification can take different forms; crowd members may also identify with social units other than the platform (e.g., with peers or with a crowdsourcing movement), and this may have a different effect on the nature of their contributions (Bagozzi and Dholakia, 2006; Hertel et al., 2003; Nambisan and Baron, 2010). In addition, scholars reported non-significant or negative associations between identification and outcomes that relate to innovation (e.g., Madjar et al., 2011; Rotondi, 1975; see Conroy et al., 2017 for a review of detrimental outcomes of identification). In light of these, I encourage further future research on how (different types of) identification influence solution appropriateness in crowdsourcing platforms.

The findings and contributions discussed above must be evaluated in the light of the limitations of this study. First, the data collected in this study were correlational in nature. Although the data enabled us to observe how naturally occurring variations in motivations were associated with solution appropriateness in the solving of real-world innovation problems, they did not allow determining precise causality. I encourage future researchers to use experimental manipulations and random assignment procedures to show more explicitly the causal role of motivation in crowdsourcing challenges. Moreover, the results presented here are based on a single crowdsourcing platform. The platform examined in this study includes a wide range of innovation problems from different disciplines and has large number of participants from all over the world; still, future research is needed to observe whether the results presented here are generalizable to other platforms for crowdsourcing challenges. It is also worth noting that the results relate to the crowdsourcing of complex innovation problems where an ideal solution needs to meet a number of requirements. Future research could explore whether the relationship between motivations and solution appropriateness unfolds in a similar way for challenges that are simpler and non-specific. On a related note, the low response rate to our survey, which is characteristic of surveys conducted on online platforms (Nambisan and Baron, 2010), raises questions about the representativeness of the sample. Although I did not find any evidence of non-response bias with our existing data, non-response bias possibility cannot be ruled out completely without having data on all participants.

Furthermore, although the solution appropriateness measure employed in this study has high external validity as it is a rating system used by a real crowdsourcing platform to filter out unsuitable ideas, one concern regarding this measure could be that non-substantive elements of a submission (e.g., writing style or grammatical accuracy) might bias the ratings. However, it is

worth noting that the submissions in InnoCentive are similar to technical or scientific reports, where these elements are likely to be of less importance. In addition, the assessors in InnoCentive are experienced in evaluating submissions from a wide range of scientific disciplines (and often have a PhD in science); they may therefore be less prone to be swayed by the way a submission is written. Despite their extensive experience, which enables them to create a rating system that is consistent across different problems, and their close connection with organizations that post challenges, the assessors are outsiders to these organizations, which might limit their ability to judge the appropriateness for a specific organization. I would encourage future research to test the link between motivation and appropriateness using other techniques to evaluate appropriateness, such as consensual assessment (Amabile, 1982; see also Acar, 2018; Miron-Spektor and Beenen, 2015), in order to expand the generalizability of the study's findings.

Finally, future research could draw on other established motivational frameworks to identify novel motivations. For example, achievement motivation theory (Dweck and Leggett, 1988; Elliot and Church, 1997) might be of value here, given the competitive nature of crowdsourcing challenges. This theory differentiates between learning orientation (i.e., motivation to improve skills) and performance orientation, which can take the form of either performance-avoid (i.e., motivation to avoid losses) or performance-prove (i.e., motivation to pursue gains). Although my model captures learning orientation, expanding that model to look more closely at the potential effects of (different forms of) performance orientation might provide a better understanding of how motivations affect the nature of the solutions generated by *crowd* members.

All in all, crowdsourcing challenges offer great potential for providing rapid solutions to innovation problems in a cost-effective manner. An important step in harnessing this potential

more effectively is to acquire a deeper understanding of what makes those in the *crowd* tick and of how those motivations affect the solutions that *crowd* members generate. I hope the insights provided in this paper will enable the remarkable creative potential of the crowd to be used more effectively to achieve innovative breakthroughs.

Acknowledgements

The data collection for this study was made possible by funding from the Erasmus Research Institute of Management. I would also like to thank InnoCentive for their generous support with the data collection for this study.

References

Acar, O.A., 2018. Harnessing the creative potential of consumers: Money, participation, and creativity in idea crowdsourcing. Mark. Lett. 29, 177–188.

Acar, O.A., Puntoni, S., 2016. Customer Empowerment in the Digital Age. J. Advert. Res. 56, 4–8. https://doi.org/10.2501/JAR-2016-007

Acar, O.A., van den Ende, J., 2016. Knowledge distance, cognitive-search processes and creativity: the making of winning solutions in science contests. Psychol. Sci. 27, 692–699.

Acar, O.A., van den Ende, J., 2015. Understanding fear of opportunism in global prize-based science contests: Evidence for gender and age differences. PLoS One 10.

Afuah, A., Tucci, C.L., 2012. Crowdsourcing as a solution to distant search. Acad. Manag. Rev. 37, 355–375.

Ales, L., Cho, S., Korpeoglu, E., 2017. Optimal Award Scheme in Innovation Tournaments. Oper. Res. 65, 693–702.

Amabile, T., 1996. Creativity in context. Westview Press, Boulder, CO.

Amabile, T.M., 1982. Social psychology of creativity: A consensual assessment technique. J. Pers. Soc. Psychol. 43, 997–1013. https://doi.org/10.1037/0022-3514.43.5.997

Amabile, T.M., Hill, K.G., Hennessey, B.A., Tighe, E.M., 1994. The Work Preference Inventory : Assessing Intrinsic and Extrinsic Motivational Orientations. J. Pers. Soc. Psychol. 66, 950–967.

Ambrose, M.L., Kulik, C.T., 1999. Old friends, new faces: Motivation research in the 1990s, Journal of Management. https://doi.org/10.1177/014920639902500302

Ashforth, B.E., Mael, F., 1989. Social identity theory and the organization. Acad. Manag. Rev. 14, 20–39.

Bagozzi, R., Dholakia, U., 2006. Open source software user communities: A study of participation in Linux user groups. Manage. Sci. 52, 1099–1115. https://doi.org/10.1287/mnsc.1060.0545

Barron, K.E., Harackiewicz, J.M., 2001. Achievement goals and optimal motivation : Testing multiple goal models. J. Pers. Soc. Psychol. 80, 706–722. https://doi.org/10.1037//0022-3514.80.5.706

Batson, C.D., Shaw, L.L., 1991. Evidence for Altruism: Toward a Pluralism of Prosocial Motives. Psychol. Inq. https://doi.org/10.1207/s15327965pli0202_1

Bayus, B.L., 2013. Crowdsourcing New Product Ideas over Time: An Analysis of the Dell IdeaStorm Community. Manage. Sci. 59, 226–244. https://doi.org/10.1287/mnsc.1120.1599

Bechtoldt, M.N., De Dreu, C.K.W., Nijstad, B.A., Choi, H.S., 2010. Motivated Information Processing, Social Tuning, and Group Creativity. J. Pers. Soc. Psychol. 99, 622–637. https://doi.org/10.1037/a0019386

Bell, B.S., Kozlowski, S., 2008. Active Learning : Effects of Core Training Design Elements on Self-Regulatory Processes , Learning , and Adaptability. J. Appl. Psychol. 93, 296–316.

Blohm, I., Leimeister, J.M., Krcmar, H., 2013. Crowdsourcing: How to Benefit from (Too) Many Great Ideas. MIS Q. Exec. 12, 199–211.

Boons, M., Stam, D., Barkema, H.G., 2015. Feelings of Pride and Respect as Drivers of Ongoing Member Activity on Crowdsourcing Platforms. J. Manag. Stud. https://doi.org/10.1111/joms.12140

Boudreau, K.J., Lacetera, N., Lakhani, K.R., 2011. Incentives and Problem Uncertainty in Innovation Contests: An Empirical Analysis. Manage. Sci. 57, 843–863. https://doi.org/10.1287/mnsc.1110.1322

Brett, J.F., VandeWalle, D., 1999. Goal orientation and goal content as predictors of performance in a training program. J. Appl. Psychol. 84, 863.

Carr, P.B., Walton, G.M., 2014. Cues of working together fuel intrinsic motivation. J. Exp. Soc. Psychol. 53, 169–184. https://doi.org/10.1016/j.jesp.2014.03.015

Chen, J., Damanpour, F., Reilly, R.R., 2010. Understanding antecedents of new product development speed: A meta-analysis. J. Oper. Manag. 28, 17–33. https://doi.org/10.1016/j.jom.2009.07.001

Conroy, S., Henle, C.A., Shore, L., Stelman, S., 2017. Where there is light, there is dark: A review of the detrimental outcomes of high organizational identification. J. Organ. Behav. 38, 184–203. https://doi.org/10.1002/job.2164

Criscuolo, P., Dahlander, L., Grohsjean, T., Salter, A., 2017. Evaluating Novelty : the Role of Panels in the Selection of R & D Projects. Acad. Manag. J. 60, 433–460. https://doi.org/10.5465/amj.2014.0861

Cyert, R.M., March, J.G., 1963. A behavioral theory of the firm. Prentice Hall, Englewood Cliffs, NJ.

Deci, E.L., Betley, G., Kahle, J., Abrams, L., Porac, J., 1981. When trying to win: Competition and intrinsic motivation. Personal. Soc. Psychol. Bull. 7, 79–83.

Dellarocas, C., 2010. Online Reputation Systems: How to Design One That Does What You Need. MIT Sloan Manag. Rev. 51, 33–37.

Dholakia, U.M., Bagozzi, R.P., Klein, L., 2004. A social influence model of consumer participation in network- and small-group-based virtual communities. Int. J. Res. Mark. 21, 241–263. https://doi.org/10.1016/j.ijresmar.2003.12.004

Dukerich, J.M., Golden, B.R., Shortell, S.M., 2002. Beauty is in the eye of the beholder: The impact of organizational identification, identity, and image on the cooperative behaviors of physicians. Adm. Sci. Q. 47, 507–533.

Dweck, C.S., Leggett, E.L., 1988. A Social-Cognitive Approach to Motivation and Personality. Psychol. Rev. 95, 256–273.

Eisenberger, R., Rhoades, L., 2001. Incremental effects of reward on creativity. J. Pers. Soc. Psychol. 81, 728–741. https://doi.org/10.1037/0022-3514.81.4.728

Eisenhardt, K.M., Graebner, M.E., 2007. Theory building from cases: Opportunities and challenges. Acad. Manag. J. 50, 25–32. https://doi.org/10.5465/AMJ.2007.24160888

Elliot, A.J., Church, M.A., 1997. A Hierarchical Model of Approach and Avoidance Achievement Motivation. J. Pers. Soc. Psychol. 72, 218–232.

Fehr, E., Gintis, H., 2007. Human Motivation and Social Cooperation: Experimental and Analytical Foundations. Annu. Rev. Sociol. 33, 43–64. https://doi.org/10.1146/annurev.soc.33.040406.131812

Frey, K., Lüthje, C., Haag, S., 2011. Whom should firms attract to open innovation platforms? The role of knowledge diversity and motivation. Long Range Plann. 44, 397–420. https://doi.org/10.1016/j.lrp.2011.09.006

Fuller, J., 2010. Refining Virtual Co-Creation from a Consumer Perspective. Calif. Manage. Rev. 52, 98–122.

Füller, J., Jawecki, G., Mühlbacher, H., 2007. Innovation creation by online basketball communities ☆. J. Bus. Res. 60, 60–71. https://doi.org/10.1016/j.jbusres.2006.09.019

Gagné, M., Deci, E.L., 2005. Self-determination theory and work motivation. J. Organ. Behav. 26, 331–362. https://doi.org/10.1002/job.322

Garcia Martinez, M., 2015. Solver engagement in knowledge sharing in crowdsourcing communities: Exploring the link to creativity. Res. Policy 44, 1419–1430. https://doi.org/10.1016/j.respol.2015.05.010

Gardner, H., 1993. Creating minds: An anatomy of creativity seen through the lives of Freud, Einstein, Picasso, Stravinsky, Eliot, Graham, and Ghandi. Basic Books (AZ), New York.

Gong, Y., Huang, J.C., Farh, J.L., 2009. Employee learning orientation, transformational leadership, and employee creativity: The mediating role of employee creative self-efficacy. Acad. Manag. J. 52, 765–778. https://doi.org/10.5465/AMJ.2009.43670890

Grant, A.M., 2012. Leading with meaning: Beneficiary contact, proscoial impact, and the performance effects of transformational leadership. Acad. Manag. J. 55, 458–476. https://doi.org/10.5465/amj.2010.0588

Grant, A.M., 2008. Does intrinsic motivation fuel the prosocial fire? Motivational synergy in predicting persistence, performance, and productivity. J. Appl. Psychol. 93, 48–58. https://doi.org/10.1037/0021-9010.93.1.48

Grant, A.M., 2007. Relational job design and the motivation to make a prosocial difference. Acad. Manag. Rev. 32, 393–417. https://doi.org/10.5465/AMR.2007.24351328

Grant, A.M., Berry, J.W., 2011. The necessity of others is the mother of invention: Intrinsic and prosocial motivations, perspective taking, and creativity. Acad. Manag. J. 54, 73–96.

https://doi.org/10.5465/AMJ.2011.59215085

Grant, A.M., Sumanth, J.J., 2009. Mission possible? The performance of prosocially motivated employees depends on manager trustworthiness. J. Appl. Psychol. 94, 927–944. https://doi.org/10.1037/a0014391

Guay, F., Vallerand, R.J., Blanchard, C., 2000. On the Assessment of Situational Intrinsic and Extrinsic Motivation: The Situational Motivation Scale (SIMS). Motiv. Emot. 24, 175–213. https://doi.org/10.1023/A:1005614228250

Hair, J.F., Black, William, C., Babin, B.J., Anderson, R.E., Tatham, R.L., 1998. Multivariate data analysis. Upper Saddle River, NJ: Prentice Hall.

Harhoff, D., Lakhani, K.R., 2016. Revolutionizing innovation: Users, communities, and open innovation. MIT Press.

Hars, A., Ou, S., 2002. Working for free? Motivations for participating in open-source projects. Int. J. Electron. Commer. 6, 25–39. https://doi.org/10.1080/10864415.2002.11044241

Hayes, J.R., 1989. Cognitive processes in creativity, in: Glover, J., Ronning, R., Reynolds, C. (Eds.), Handbook of Creativity. Plenum, New York, pp. 135–145.

Hennessey, B.A., Amabile, T., 2010. Creativity. Annu. Rev. Psychol. 61, 569–598. https://doi.org/10.1146/annurev.psych.093008.100416

Hertel, G., Niedner, S., Herrmann, S., 2003. Motivation of software developers in open source projects: An Internet-based survey of contributors to the Linux kernel. Res. Policy 32, 1159–1177. https://doi.org/10.1016/S0048-7333(03)00047-7

Hofstetter, R., Zhang, J.Z., Herrmann, A., 2017. Successive Open Innovation Contests and Incentives: Winner-Take-All or Multiple Prizes? J. Prod. Innov. Manag. 00.

https://doi.org/10.1111/jpim.12424

Howe, J., 2006. The rise of crowdsourcing. Wired Mag. 14, 1–4.

Huang, Y., Singh, P., Srinivasan, K., 2014. Crowdsourcing New Product Ideas Under Consumer Learning. Manage. Sci. 60, 2138–2159.

Jeppesen, L.B., Frederiksen, L., 2006. Why Do Users Contribute to Firm-Hosted User Communities? The Case of Computer-Controlled Music Instruments. Organ. Sci. 17, 45–63. https://doi.org/10.1287/orsc.1050.0156

Jeppesen, L.B., Lakhani, K.R., 2010. Marginality and Problem-Solving Effectiveness in Broadcast Search. Organ. Sci. 21, 1016–1033. https://doi.org/10.1287/orsc.1090.0491

Lakhani, K R, Boudreau, K J, Loh-P-R, Backstrom, L, Baldwin, C, Lonstein, E, Lydon, M, MacCormack, A, Arnaout, R A, Guinan, E., 2013. Prize-based contests can provide to solutions to computational biology problems. Nat. Biotechnol. 31, 108–111. https://doi.org/10.14440/jbm.2015.54.A

Lakhani, K.R., Boudreau, K.J., 2013. Using the Crowd as an Innovation Partner. Harv. Bus. Rev.

Lakhani, K.R., Jeppesen, L.B., Lohse, P. a, Panetta, J. a, 2007. The Value of Openness in Scientific Problem Solving, HBS Working Paper Number: 07-050. https://doi.org/10.1007/s00268-006-0616-1

Lakhani, K.R., Wolf, R.G., 2005. Why Hackers Do What They Do : Understanding Motivation and Effort in Free / Open Source Software Projects 1 By. Perspect. Free Open Source Softw. 1–27. https://doi.org/10.2139/ssrn.443040

Le Bouc, R., Pessiglione, M., 2013. Imaging Social Motivation: Distinct Brain Mechanisms Drive Effort Production during Collaboration versus Competition. J. Neurosci. 33, 15894–

15902. https://doi.org/10.1523/JNEUROSCI.0143-13.2013

Leimester, J., Huber, M., Bretschneider, U., Krcmar, H., 2009. Leveraging Crowdsourcing : Activation-Supporting Components for IT-Based Ideas Competition. J. Manag. Inf. Syst. 26, 197–224. https://doi.org/10.2753/MIS0742-

Li, Q., Maggitti, P.G., Smith, K., Tesluk, P.E., Katila, R., 2013. Top management attention to innovation: The role of search selection and intensity in new product introductions. Acad. Manag. J. 56, 893–916. https://doi.org/10.5465/amj.2010.0844

Lifshitz-Assaf, H., 2017. Dismantling Knowledge Boundaries at NASA: The Critical Role of Professional Identity in Open Innovation. Adm. Sci. Q. https://doi.org/10.1177/0001839217747876

Liu, D., Jiang, K., Shalley, C.E., Keem, S., Zhou, J., 2016. Motivational mechanisms of employee creativity : A meta-analytic examination and theoretical extension of the creativity literature. Organ. Behav. Hum. Decis. Process. 137, 236–263. https://doi.org/10.1016/j.obhdp.2016.08.001

Lüthje, C., 2004. Characteristics of innovating users in a consumer goods field: An empirical study of sport-related product consumers. Technovation 24, 683–695. https://doi.org/10.1016/S0166-4972(02)00150-5

Madjar, N., Greenberg, E., Chen, Z., 2011. Factors for radical creativity, incremental creativity, and routine, noncreative performance. J. Appl. Psychol. 96, 730–743. https://doi.org/10.1037/a0022416

Mair, P., Hofmann, E., Gruber, K., Hatzinger, R., Zeileis, A., Hornik, K., 2015. Motivation, values, and work design as drivers of participation in the R open source project for

statistical computing. Proc. Natl. Acad. Sci. 112, 14788–92. https://doi.org/10.1073/pnas.1506047112

Majchrzak, A., Malhotra, A., 2013. Towards an information systems perspective and research agenda on crowdsourcing for innovation. J. Strateg. Inf. Syst. 22, 257–268. https://doi.org/10.1016/j.jsis.2013.07.004

Malinen, S., 2015. Understanding user participation in online communities : A systematic literature review of empirical studies. Comput. Human Behav. 46, 228–238. https://doi.org/10.1016/j.chb.2015.01.004

March, J.G., Simon, H.A., 1958. Organizations.

McLean, K., Pasupathi, M., Pals, J., 2007. Selves Creating Stories Creating Selves : A Process Model of Self-Development. Personal. Soc. Psychol. Rev. 11, 262–278. https://doi.org/10.1177/1088868307301034

Mehta, R., Zhu, R. (Juliet), Cheema, A., 2012. Is Noise Always Bad? Exploring the Effects of Ambient Noise on Creative Cognition. J. Consum. Res. 39, 784–799. https://doi.org/10.1086/665048

Miron-Spektor, E., Beenen, G., 2015. Motivating creativity : The effects of sequential and simultaneous learning and performance achievement goals on product novelty and usefulness. Organ. Behav. Hum. Decis. Process. 127, 53–65. https://doi.org/10.1016/j.obhdp.2015.01.001

Murray, F., Stern, S., Campbell, G., MacCormack, A., 2012. Grand Innovation Prizes: A theoretical, normative, and empirical evaluation. Res. Policy 41, 1779–1792. https://doi.org/10.1016/j.respol.2012.06.013

Nambisan, S., Baron, R.A., 2010. Different Roles, Different Strokes: Organizing Virtual Customer Environments to Promote Two Types of Customer Contributions. Organ. Sci. 21, 554–572. https://doi.org/10.1287/orsc.1090.0460

Nambisan, S., Baron, R.A., 2009. Virtual customer environments: Testing a model of voluntary participation in value co-creation activities. J. Prod. Innov. Manag. 26, 388–406. https://doi.org/10.1111/j.1540-5885.2009.00667.x

Nambisan, S., Lyytinen, K., Majchrzak, A., Song, M., 2017. Digital innovation management: Reinventing innovation management research in a digital world. MIS Q. 41, 223–238. https://doi.org/10.25300/MISQ/2017/41

Nishikawa, H., Schreier, M., Ogawa, S., 2013. User-generated versus designer-generated products: A performance assessment at Muji. Int. J. Res. Mark. 30, 160–167. https://doi.org/10.1016/j.ijresmar.2012.09.002

Ocasio, W., 1997. Towards an attention-based view of the firm. Strateg. Manag. J. 187–206.

Perry-Smith, J.E., Shalley, C., 2003. The social side of creativity: A static and dynamic social perspective. Acad. Manag. Rev. 28, 89–106.

Piezunka, H., Dahlander, L., 2018. Idea Rejected, Tie Formed: Organizations' Feedback on Crowdsourced Ideas. Acad. Manag. J. amj.2016.0703. https://doi.org/10.5465/amj.2016.0703

Piezunka, H., Dahlander, L., 2014. Distant Search, Narrow Attention: How Crowding Alters Organizations ' Filtering of Suggestions in Crowdsourcing. Acad. Manag. J. 58, 856–880. https://doi.org/10.5465/amj.2012.0458

Poetz, M.K., Schreier, M., 2012. The value of crowdsourcing: Can users really compete with

professionals in generating new product ideas? J. Prod. Innov. Manag. 29, 245–256. https://doi.org/10.1111/j.1540-5885.2011.00893.x

Prendergast, C., 1999. The provision of incentives in firms. J. Econ. Lit. 37, 7–63. https://doi.org/10.1257/jel.37.1.7

Riketta, M., 2005. Organizational identification: A meta-analysis. J. Vocat. Behav. 66, 358–384.

Roberts, J. a., Hann, I.-H., Slaughter, S. a., 2006. Understanding the Motivations, Participation, and Performance of Open Source Software Developers: A Longitudinal Study of the Apache Projects. Manage. Sci. 52, 984–999. https://doi.org/10.1287/mnsc.1060.0554

Rogelberg, S.G., Stanton, J.M., 2007. Introduction: Understanding and Dealing With Organizational Survey Nonresponse. Organ. Res. Methods 10, 195–209. https://doi.org/10.1177/1094428106294693

Rotondi, T., 1975. Organizational Identification: Issues and Implications. Organ. Behav. Perform. 13, 95–109. https://doi.org/10.1016/0030-5073(75)90007-0

Runco, M.A., 2004. Creativity. Annu. Rev. Psychol. 55, 657–687. https://doi.org/10.1146/annurev.psych.55.090902.141502

Runco, M.A., Charles, R.E., 1993. Judgments of originality and appropriateness as predictors of creativity. Pers. Individ. Dif. 15, 537–546.

Ryan, R.M., Connell, J.P., 1989. Perceived locus of causality and internalization: Examining reasons for acting in two domains. J. Pers. Soc. Psychol. 57, 749–761. https://doi.org/10.1037/0022-3514.57.5.749

Ryan, R.M., Deci, E.L., 2000. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. Am. Psychol. 55, 68–78.

https://doi.org/10.1037/0003-066X.55.1.68

Rynes, S.L., Gerhart, B., Parks, L., 2005. Personnel psychology: performance evaluation and pay for performance. Annu. Rev. Psychol. 56, 571–600. https://doi.org/10.1146/annurev.psych.56.091103.070254

Saez-Rodriguez, J., Costello, J.C., Friend, S.H., Kellen, M.R., Mangravite, L., Meyer, P., Norman, T., Stolovitzky, G., 2016. Crowdsourcing biomedical research : leveraging communities as innovation engines. Nat. Rev. Genet. 17, 470–486. https://doi.org/10.1038/nrg.2016.69

Sauermann, H., Cohen, W.M., 2010. What Makes Them Tick? Employee Motives and Firm Innovation. Manage. Sci. 56, 2134–2153.

Sauermann, H., Roach, M., 2013. Increasing web survey response rates in innovation research: An experimental study of static and dynamic contact design features. Res. Policy 42, 273–286. https://doi.org/10.1016/j.respol.2012.05.003

Schau, H.J., Muñiz, A.M., Arnould, E.J., 2009. How Brand Community Practices Create Value. J. Mark. 73, 30–51.

Schemmann, B., Herrmann, A.M., Chappin, M.M.H., Heimeriks, G.J., 2016. Crowdsourcing ideas: Involving ordinary users in the ideation phase of new product development. Res. Policy 45, 1145–1154. https://doi.org/10.1016/j.respol.2016.02.003

Shalley, C., Zhou, J., Oldham, G.R., 2004. The effects of personal and contextual characteristics on creativity: Where should we go from here? J. Manage. 30, 933–958. https://doi.org/10.1016/j.jm.2004.06.007

Simons, P., De Jong, F.P.C.M., 1992. Self-regulation and Computer-aided Instruction. Appl.

Psychol. 41, 333–346.

Smidts, A., Pruyn, A., Van Riel, C., 2001. the Impact of Employee Communication and Perceived External Prestige on Organizational Identification. Acad. Manag. J. 44, 1051–1062. https://doi.org/10.2307/3069448

Stahlbrost, A., Kareborn, B.B., 2011. Exploring users motivation in innovation communities. Int. J. Entrep. Innov. Manag. 14, 298. https://doi.org/10.1504/IJEIM.2011.043051

Tajfel, H., 1978. The achievement of group differentiation, in: Tajfel, H. (Ed.), Differentiation between Social Groups: Studies in the Social Psychology of Intergroup Relations. Academic Press, London, pp. 77–98.

Terwiesch, C., Xu, Y., 2008. Innovation Contests, Open Innovation, and Multiagent Problem Solving. Manage. Sci. 54, 1529–1543. https://doi.org/10.1287/mnsc.1080.0884

Von Krogh, G., 2012. How does social software change knowledge management? Toward a strategic research agenda. J. Strateg. Inf. Syst. 21, 154–164. https://doi.org/10.1016/j.jsis.2012.04.003

von Krogh, G., Haefliger, S., Spaeth, S., Wallin, M.W., 2012. Carrots and Rainbows: Motivation and Social Practice in Open Source Software Development. MIS Q. 36, 649–676.

Wrzesniewski, A., Schwartz, B., Cong, X., Kane, M., Omar, A., Kolditz, T., 2014. Multiple types of motives don ' t multiply the motivation of West Point cadets. Proc. Natl. Acad. Sci. 1–6. https://doi.org/10.1073/pnas.1405298111

Wu, C.G., Gerlach, J.H., Young, C.E., 2007. An empirical analysis of open source software developers' motivations and continuance intentions. Inf. Manag. 44, 253–262. https://doi.org/10.1016/j.im.2006.12.006

Yang, H., Chattopadhyay, A., Zhang, K., Dahl, D.W., 2012. Unconscious creativity: When can unconscious thought outperform conscious thought? J. Consum. Psychol. 22, 573–581. https://doi.org/10.1016/j.jcps.2012.04.002

Table 1. Means, Standard Deviations and Correlations[a]

Variable	*M*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1. Prize size	4.38	.25							
2. Number of submissions	104.21	102.4	-.39**						
3. Duration (days)	71.2	40.83	.26**	-.14**					
4. Challenge type	.17	.38	.48**	-.31**	.46**				
5. Recency (days)	317.75	220.49	.03	-.25**	.17**	.07			
6. Outcome awareness	0.48	.50	-.16**	.07	-.12**	-.10*	.70**		
7. Knowledge distance	4.05	1.89	-.08	.11**	-.08	-.10**	-.01	.01	
8. PhD degree	.32	.47	.13**	-.23**	.00	.12**	.03	-.01	-.13**
9. Associate degree	.09	.29	-.10*	.13**	.03	-.08	-.01	.02	-.02
10. Bachelors degree	.23	.42	-.03	.04	-.06	-.08	.05	.07	.07
11. Masters degree	.24	.43	.03	.02	.07	.06	-.03	-.04	.04
12. Intrinsic motivation	5.53	1.30	-.04	.08*	.00	-.03	.02	.02	.06
13. Learning motivation	4.94	1.69	.01	.02	.04	.05	-.04	-.07	.01
14. Prosocial motivation	5.41	1.47	-.01	.08*	.03	-.04	-.04	-.07	-.04
15. Extrinsic motivation	4.44	1.38	.08	-.05	.02	.10**	-.15**	-.13**	-.04
16. Social motivation	4.13	1.56	.02	-.01	.01	-.01	.01	-.03	-.05
17. Solution appropriateness	2.59	1.13	.03	-.07	.05	.08*	-.03	-.06	-.18**

Variable	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*
9. Associate degree	-.22**								
10. Bachelors degree	-.38**	-.18**							
11. Masters degree	-.39**	-.18**	-.31**						
12. Intrinsic motivation	-.13**	.06	.03	.05					
13. Learning motivation	-.14**	.07	.02	.03	.63**				
14. Prosocial motivation	-.12**	.09*	-.02	.04	.56**	.55**			
15. Extrinsic motivation	.00	-.02	-.02	.05	.25**	.32**	.32**		
16. Social motivation	-.05	.03	-.01	.04	.30**	.33**	.27**	.20**	
17. Solution appropriateness	.21**	-.11**	-.08*	.07	-.03	-.13**	-.13**	-.03	.05

[a]Pairwise deletion.The prize size variable is log-transformed. * $p < .05$, ** $p < .01$ (two-tailed test)

Table 2. Results of the OLS Regression Analyses Predicting Solution Appropriateness[a]

Variables	**Model 1**	**Model 2[b]**
	β (SE)	β (SE)
Prize size	-.063 (.209)	-.060 (.206)
Number of submissions	.055 (.001)	.053 (.001)
Duration	.013 (.000)	.019 (.000)
Challenge type	.049 (.152)	.052 (.151)
Recency	-.009 (.000)	-.022 (.000)
Outcome awareness	-.055 (.143)	-.063 (.141)
Associate degree	.092† (.206)	.088† (.202)
Bachelor's degree	.253*** (.176)	.235*** (.174)
Master's degree	.337*** (.174)	.320*** (.172)
PhD degree	.450*** (.172)	.420*** (.170)
Knowledge distance	-.156*** (.024)	-.164*** (.024)
Intrinsic motivation		.151** (.047)
Learning motivation		-.164** (.037)
Prosocial motivation		-.109* (.039)
Social motivation		-.018 (.036)
Extrinsic motivation		.117** (.030)
Adjusted *R* squared	.101	.131
F of change	6.825***	4.900***

[a] Values are standardized coefficients. Standard errors are in parentheses. Prize size is log-transformed.
[b] The results are robust to exclusion of control variables.
$^{\dagger}p < .10$ $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Appendix A. Results of Exploratory Factor Analysis with All Items[a]

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Intellectual curiosity*	0.357	-0.199	0.069	0.006	0.57
Enjoyment of working in the field of the challenge*	0.372	-0.011	0.128	-0.033	0.436
Enjoyment of creating new things	0.265	-0.035	0.043	-0.126	0.629
Enjoyment of solving problems	0.093	-0.053	0.006	-0.082	0.814
Feelings of being intellectually challenged	0.128	0.141	-0.02	0.009	0.732
Feelings of satisfaction from beating other solvers*	-0.173	0.453	0.077	-0.071	0.384
Feelings of satisfaction from being able to solve a problem	-0.041	0.088	-0.054	-0.234	0.709
Opportunity to work on something that matters	-0.089	0.058	0.058	-0.885	0.115
Opportunity to work on 'real-life' problems	-0.017	0.042	0.116	-0.767	0.137
Opportunity to benefit others through my solution	0.107	-0.076	0.002	-0.847	0.019
Being a part of changing the way the world innovates*	0.385	0.057	0.091	-0.53	-0.031
Learning new things	0.704	-0.051	0.133	-0.071	0.221
Enhancing my skills	0.731	0.04	0.082	-0.079	0.208
Sharpening my brain	0.712	0.064	0.122	0.012	0.201
Being updated with science	0.72	0.04	-0.001	-0.116	0.155
Using my time in a good way**	0.717	0.072	0.063	-0.1	0.007
Feedback from InnoCentive or the seeker*	0.37	0.359	-0.002	-0.18	-0.138
I feel strong ties with InnoCentive.	0.032	-0.035	0.877	-0.099	-0.13
I experience a strong sense of belonging to InnoCentive.	0.042	-0.008	0.89	-0.102	-0.138
I feel proud to work for InnoCentive.	0.02	0.06	0.800	-0.116	0.029
I am sufficiently acknowledged in InnoCentive.	-0.023	0.053	0.746	0.27	0.081
I am glad to be a member of InnoCentive.	0.031	-0.04	0.727	-0.103	0.043
Improving my resumé*	0.313	0.775	-0.068	0.07	-0.04
Enhancing my career/business prospects	0.209	0.818	-0.083	-0.032	-0.091
Recognition I will receive after solving the problem	-0.027	0.784	0.074	-0.067	0.07
Showing my competencies	0.058	0.718	0.098	-0.045	0.131
Potential future income from the seeker	-0.053	0.738	-0.007	-0.105	-0.089
Award money	-0.194	0.657	0.076	0.146	0.063

[a]Pattern matrix (N = 328). * Item removed due to factor loadings; ** Item removed due to face validity.

Appendix B. Results of Exploratory Factor Analysis after Item Reduction[a]

	Intrinsic Motivation	Prosocial Motivation	Learning Motivation	Social Motivation	Extrinsic Motivation
Enjoyment of creating new things	**0.583**	-0.117	0.275	-0.05	-0.053
Enjoyment of solving problems	**0.891**	-0.044	0.027	-0.015	-0.064
Feelings of being intellectually challenged	**0.759**	0.058	0.118	0.007	0.108
Feelings of satisfaction from being able to solve a problem	**0.72**	-0.193	0.008	0.032	0.032
Opportunity to work on something that matters	0.118	**-0.879**	-0.048	-0.062	0.09
Opportunity to work on 'real-life' problems	0.135	**-0.772**	0.01	-0.117	0.085
Opportunity to benefit others through my solution	0.025	**-0.806**	0.139	0	-0.07
Learning new things	0.077	-0.009	**0.851**	-0.087	-0.064
Enhancing my skills	0.049	0	**0.905**	-0.029	0.038
Sharpening my brain	0.038	0.065	**0.885**	-0.049	0.055
Being updated with science	0.043	-0.072	**0.809**	0.041	0.031
I feel strong ties with InnoCentive.	-0.139	-0.081	0.076	**-0.865**	-0.011
I experience a strong sense of belonging to InnoCentive.	-0.14	-0.126	0.032	**-0.882**	0.011
I feel proud to work for InnoCentive.	0.067	-0.122	-0.007	**-0.800**	0.083
I am sufficiently acknowledged in InnoCentive.	0.106	0.25	-0.01	**-0.733**	0.007
I am glad to be a member of InnoCentive.	0.096	-0.083	0.03	**-0.725**	-0.033
Enhancing my career/business prospects	-0.113	-0.073	0.217	0.089	**0.764**
Recognition I will receive after solving the problem	0.026	-0.098	-0.009	-0.056	**0.786**
Showing my competencies	0.113	-0.03	0.097	-0.076	**0.741**
Potential future income from the seeker	-0.082	-0.069	-0.01	0.033	**0.814**
Award money	0.122	0.196	-0.171	-0.059	**0.722**

[a]Pattern matrix (N = 328).