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Solvers' participation in crowdsourcing platforms: Examining the impacts of trust, and benefit and cost factors

Hua (Jonathan) Ye [a,*], Atreyi Kankanhalli [b]

[a] Department of Information Systems and Operations Management, The University of Auckland, 12 Grafton Road, Auckland 1142, New Zealand
[b] Department of Information Systems, National University of Singapore, Singapore

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ABSTRACT

Organizations are increasingly crowdsourcing their tasks to unknown individual workers, i.e., solvers. Solvers' participation is critical to the success of crowdsourcing activities. However, challenges exist in attracting solvers to participate in crowdsourcing. In this regard, prior research has mainly investigated the influences of benefit factors on solvers' intention to participate in crowdsourcing. Thus, there is a lack of understanding of the cost factors that influence actual participation behavior, in conjunction with the benefits. Additionally, the role of trust in the cost-benefit analysis remains to be explored. Motivated thus, based on social exchange theory and context-related literature, we develop a model to explain the impacts of benefit and cost factors as well as trust on solver participation behavior in crowdsourcing. The model was tested using survey and archival data from 156 solvers on a large crowdsourcing platform. As hypothesized, monetary reward, skill enhancement, work autonomy, enjoyment, and trust were found to positively affect solvers' participation in crowdsourcing, while cognitive effort negatively affects their participation. In addition, it was found that monetary reward positively affects trust (trust partially mediates its effect on participation behavior), while loss of knowledge power negatively affects trust. The theoretical contributions and practical implications of the study are discussed.

Introduction

The large-scale interconnectivity afforded through Internet-based technologies has transformed how organizational tasks are being performed (Deng et al., 2016; Geri et al., 2017). Firms are increasingly leveraging the wisdom of crowds to perform a variety of tasks, e.g., to obtain market feedback about products, undertake tedious work, and collect novel ideas (Piezunka and Dahlander, 2015; Ye and Kankanhalli, 2015). This phenomenon of crowdsourcing is defined as the act of recruiting a large group of undefined individuals, i.e., solvers, to undertake organizational tasks through Internet-based platforms (Howe, 2008). Strategically, crowdsourcing is considered as an important opportunity by businesses to gain external expertise and lower their costs (Kietzmann, 2017). With innovation and talent management being major strategic priorities for CEOs (KPMG, 2016), crowdsourcing serves as a way to foster organizational innovation through tapping external solvers' knowledge and creativity (Majchrzak and Malhotra, 2013).

* Corresponding author.
E-mail addresses: Jonathan.ye@auckland.ac.nz (H.(J.) Ye), Atreyi@comp.nus.edu.sg (A. Kankanhalli).

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Indeed, participation of solvers is critical to the viability and success of crowdsourcing (Afuah and Tucci, 2012; Boons et al., 2015). However, challenges exist in sustaining solver participation in crowdsourcing (Boons et al., 2015; Greengard, 2011), such as the difficulty of motivating solver participation with appropriate incentives (Majchrzak and Malhotra, 2013). With varied incentives being proposed (Geri et al., 2017; Kaufman et al., 2011), monetary reward alone may not be sufficient to motivate solvers to participate (Feller et al., 2012; Zheng et al., 2011). Further, the costs incurred during crowdsourcing need to be identified and addressed. Without knowledge of the antecedents of solvers' participation, the performance of crowdsourcing may be undermined (Afuah and Tucci, 2012; Boons et al., 2015). Thus, it is important for firms and crowdsourcing platforms to understand what motivates and inhibits solvers from participating in crowdsourcing.

To date, a few studies have examined solvers' participation in crowdsourcing conceptually (e.g., Terwiesch and Xu, 2008) and empirically (e.g., Boons et al., 2015; Deng et al., 2016; Zheng et al., 2011). However, prior research has mainly focused on the influences of expected benefits (extrinsic or intrinsic motivations) on solvers' *intention* to participate in crowdsourcing. There is a need for theoretically-driven empirical research which investigates the influence of benefit factors on solvers' *actual* participation in crowdsourcing, as there could be a gap between intention and actual behavior (Sheeran and Webb, 2016). Furthermore, it has been suggested that participation in crowdsourcing may incur costs in terms of spending time and effort to understand the problems and propose solutions (Afuah and Tucci, 2012). Such costs can hinder solvers' participation in crowdsourcing, especially in the context of financially rewarded competition-based crowdsourcing (Ye and Kankanhalli, 2013). Yet there is a lack of research that identifies and empirically examines the influence of cost factors on solvers' *actual* participation in crowdsourcing.

Additionally, solvers may encounter risks such as firms' opportunistic behaviors (e.g., rejecting their solutions to tasks and not paying them) and their ideas being revealed to peers (other solvers) (Afuah and Tucci, 2012; Feller et al., 2012). Such risks heighten the importance of trust during solvers' participation. Previous research suggests that in online environments, trust can encourage participation (Jarvenpaa et al., forthcoming; Kim, 2014) and may mediate the relationship between environmental conditions and future participation (e.g., Porter and Donthu, 2008). However, there is a lack of research that explains the direct and mediating impacts of trust on solvers' participation in crowdsourcing. Thus, combined together, there is a need to examine the influences of costs and benefits on solvers' participation in crowdsourcing in conjunction with the effects of trust.

Motivated by these knowledge gaps, this study aims to answer the research questions: (1) How do trust, cost, and benefit factors affect solvers' participation in crowdsourcing? and (2) Does trust mediate the effects of certain benefit and cost factors on solvers' participation? Considering the plurality of crowdsourcing types, we focus on the common approach of financially rewarded competition-based crowdsourcing instead of voluntary collaboration-based crowdsourcing, which may be mainly intrinsically motivated (Boons et al., 2015; Ye and Kankanhalli, 2013). Based on social exchange theory (Blau, 1964) and context-related literature, we develop a model to explain solvers' participation in crowdsourcing in terms of perceived costs, benefits, and trust in the crowdsourcing platform. The model is tested with survey and archival data from 156 solvers in a large crowdsourcing platform and found to be largely supported.

This study contributes to the crowdsourcing literature by examining solvers' actual participation behavior in crowdsourcing, modeling and testing the influences of cost concerns in addition to benefits on solver participation, and exploring the role of trust in this context. It also provides insights to practitioners for attracting and sustaining solvers' participation in crowdsourcing platforms.

Conceptual background

We first review existing empirical studies and theories that explain solvers' intention to participate in crowdsourcing. From the review, we identify the research gap this study seeks to address. We then describe our theoretical foundation, social exchange theory, and justify why we use it in this study. While social exchange theory provides the overarching logic for our model, we make use of other relevant literature for more specific theorizing of the constructs in our study context. We subsequently review this literature to identify relevant benefit and cost factors for solvers' participation. Last, we build on previous literature on trust in technology to identify antecedents and effects of trust in the context of crowdsourcing participation.

Review of studies on solvers' crowdsourcing participation intention

Through our literature review, we identified several theories i.e., value theory, value expectancy theory, motivation theory, social identity theory, and value sensitive design theory, that have been applied to explain solvers' participation intention or continuance in crowdsourcing (see Table 1). Deriving from value theory, Sun et al. (2011) conducted a survey in TaskCN, a Chinese crowdsourcing website and found that hedonic value (enjoyment) enhances solvers' continuance intention. This relationship was partially mediated by satisfaction with the process of crowdsourcing. Following the previous study, Sun et al. (2012) developed a model for solvers' continuance intention based on value expectancy theory. Their survey study of solvers from TaskCN reported that both extrinsic (monetary reward) and intrinsic (enjoyment) motivations enhance solvers' intention to continue participating in crowdsourcing. In a similar vein, Zheng et al. (2011) used motivation theory and found that both intrinsic motivation (enjoyment) and the extrinsic motivation to gain recognition enhance solvers'

Table 1
Theories used to explain solvers' participation in crowdsourcing.

Theories	Proposition	Results	Reference
Value theory	People are motivated to act by judging the value of the action. There are two types of value, i.e., utilitarian and hedonic (enjoyment)	Hedonic value → satisfaction; Hedonic value, satisfaction → continuance intention	Sun et al. (2011)
Value expectancy theory	Individuals' actions are related to their *subjective value* of behavioral outcomes and the *expectancy or probability* to conduct the behavior successfully and achieve outcomes. As expectancy increases, effect of value on behavioral intention increases	Extrinsic motivation (monetary reward), intrinsic motivation (enjoyment) → continuance intention	Sun et al. (2012)
Motivation theory	People are driven to achieve their goals by their motivations. Motivation can be intrinsic and extrinsic	Extrinsic motivation to gain recognition, intrinsic motivation (enjoyment) → participation intention	Zheng et al. (2011)
		Awareness of rewards, prestige, reciprocity → content-adding	Geri et al. (2017)
Social identity theory	Individuals' identity is based on their group membership. The group which an individual belongs to is an important source of pride and self-esteem	Pride → level of member activity	Boons et al. (2015)
Value sensitive design theory	Human values should be accounted for in the design of computer technologies	Nine values shared by solvers on Amazon's Mechanical Turk are uncovered	Deng et al. (2016)

participation intention in TaskCN. Based on the same theory, Geri et al. (2017) conducted surveys on three different crowdsourcing platforms and reported the positive impacts of reward awareness, prestige, and reciprocity on individual's self-reported content-adding behaviors. Another survey study by Boons et al. (2015) used social identity theory to explain the impact of pride on members' level of activity in a crowdsourcing platform. Other than these quantitative studies, Deng et al. (2016) used value sensitive design theory to guide their interpretive field study and uncovered nine shared values of crowd workers, i.e., access, autonomy, fairness, transparency, communication, security, accountability, making an impact, and dignity.

Table 1 shows that existing research mainly examines the impacts of potential *benefits* on solvers' *intention* to participate in crowdsourcing. In other words, there is a lack of research on: (1) the antecedents of solvers' *actual* participation behavior (which may differ from participation intention), (2) the identification and influences of cost concerns, and (3) the mediating effect of trust on their participation. As the theories in Table 1 are able to explain the influences of benefits on solvers' participation, but not the impacts of costs, to address the gap, we draw on social exchange theory to explain the phenomenon.

Social exchange theory

Social exchange theory explains human behavior in social exchanges (Blau, 1964) from a cost-benefit perspective (Kankanhalli et al., 2005). It posits that individuals behave in ways that maximize benefits obtained and minimize costs from an exchange (Molm, 1997) and that they take part in an exchange only when they expect rewards to exceed the costs incurred (Gefen and Ridings, 2002). Social exchange is not governed by explicit rules or agreements. In such exchanges, people do others a favor with a general expectation of some future return but no clear expectation of what that return will be. This belief of future returns is central to a social exchange, because the lack of explicit rules and regulations means that people rely on this belief to justify their expected benefits from the exchange. Therefore, social exchange assumes the existence of relatively long-term relationships of interest as opposed to one-off exchanges (Molm, 1997).

These principles of social exchange, i.e., a cost/benefit analysis of exchange, have been used to understand knowledge sharing phenomena in online communities and organizations (Hsu et al., 2007; Wasko and Faraj, 2005; Ye et al., 2015). They suggest that members will contribute to the organization or community as long as they obtain net benefits from their contributions such as reputation, recognition, and enjoyment from helping others (Kankanhalli et al., 2005), or expect others to return their favors in the future due to reciprocity (Feng and Ye, 2016; Geri et al., 2017). Social exchange theory has been used to understand knowledge sharing behavior in various contexts. For example, Kankanhalli et al. (2005) applied the theory to explain the usage of electronic knowledge repositories (EKRs) by employees to contribute knowledge, while Ye et al. (2015) utilized social exchange theory to examine knowledge contribution in a variety of online communities.

In the context of crowdsourcing, solvers submit solutions (knowledge) to crowdsourced problems (Ye and Kankanhalli, 2015). Fundamentally, crowdsourcing participation is a type of knowledge contribution, though the specific costs and benefits of such contribution may depend on the context (Ye and Kankanhalli, 2013; Leimeister et al., 2009). Specifically, solvers are likely to base their decision on evaluating the benefits and costs of participation (e.g., money obtained vs. time and effort spent). For example, they may consider whether their solutions will win rewards and if the value of their proposals will be fairly acknowledged (Afuah and Tucci, 2012). Thus, we consider social exchange theory as an appropriate theoretical lens to explain solvers' participation in crowdsourcing since it posits that individuals will participate in such platforms based on a cost-benefit analysis of the exchange.

We use social exchange theory as an overarching theory to guide our model development. However, while social exchange theory provides the general logic for the model, other context-related literature is used to ground more specific theorizing of the model constructs and relationships. Thus, we review previous crowdsourcing and knowledge management literature to identify the specific benefit and cost factors relevant to solvers' participation in crowdsourcing.

Benefits of participation in crowdsourcing

Other than the survey studies (e.g., Sun et al., 2012; Boons et al., 2015; Geri et al., 2017) discussed above, a few case studies (e.g., Brabham, 2008, 2010; Leimeister et al., 2009) have described various motivations of solvers' participation in crowdsourcing. Apart from motivations such as winning monetary awards, gaining reputation, and enjoyment, the case studies suggest that solvers may also be motivated by other benefits, such as skill enhancement (Brabham, 2008) and work autonomy (Brabham, 2010; Deng et al., 2016). Additionally, Kaufman et al. (2011), through a survey of Mechanical Turk workers, ranked various motivations of solver participation. With a number of motivational factors being previously suggested, it is important to make sense of the salient factors through a theoretically-grounded empirical study.

Based on our review (see Table 2), the five expected benefits were identified and included as antecedents of solvers' participation in our model. From our review, we see that there is a lack of research identifying and examining the influences of cost factors and trust on solvers' participation in crowdsourcing. As per social exchange theory, expected costs will be considered in the cost-benefit calculation before initiating an exchange and should affect individuals' behavior (Molm, 1997; Wasko and Faraj, 2005; Ye et al., 2015). Further, prior research suggests that trust plays an important role in predicting people's behaviors in online environments (Jarvenpaa et al., forthcoming). Thus, we will investigate the influences of costs and trust in addition to benefit factors in our model of solvers' participation in crowdsourcing.

Costs of participation

Previous studies have suggested that solvers can incur costs when participating in crowdsourcing (e.g., Afuah and Tucci, 2012; Doan et al., 2011). From Tables 1 and 2, however, we see a lack of empirical studies identifying and examining the influence of cost factors on solvers' participation in crowdsourcing. To address the gap, we draw from the knowledge management literature to identify possible cost factors. This is because solvers' contribution of solutions to crowdsourcing tasks can be perceived as a form of online knowledge contribution (Leimeister et al., 2009).

The knowledge management literature suggests that knowledge sharing could incur the costs of loss of knowledge power and cognitive effort for knowledge contributors (Cillo, 2005; Kankanhalli et al., 2005). These costs have been suggested to discourage individual's knowledge contribution. In the context of crowdsourcing, too, solvers are likely to expend time and effort to solve tasks and contribute their solutions (Afuah and Tucci, 2012). Also, they may perceive loss of power associated with the knowledge that they have shared. As per social exchange theory, the existence of such costs may harm exchanges and discourage individuals' future participation in such exchanges (Blau, 1964). Thus, we expect these costs i.e., loss of knowledge power and cognitive effort, to hinder solvers' participation in crowdsourcing.

In addition to the cost-benefit analysis mentioned above, participation in crowdsourcing could be determined by solvers' trust in the crowdsourcing platform (Feller et al., 2012). Thus, we include trust in the crowdsourcing platform in our model, which is explained next.

Table 2
Benefits of solvers' participation from prior studies.

Constructs	Context (Study Nature: Platform)	Reference
Monetary reward (reward or its awareness)	Case study: Istockphoto	Brabham (2008)
	Case study: Threadless	Brabham (2010)
	Field study: Mechanical turk (ranking of motivations)	Kaufman et al. (2011)
	Field study: TaskCN	Sun et al. (2012)
	Field study: 3 platforms	Geri et al. (2017)
Skill enhancement (human capital advancement)	Case study: Istockphoto	Brabham (2008)
	Case study: Threadless	Brabham (2010)
	Case study: SAPien community	Leimeister et al. (2009)
	Field study: Mechanical turk (ranking of motivations)	Kaufman et al. (2011)
Peer reputation (acknowledgement/ prestige from peers)	Case study: Istockphoto	Brabham (2008)
	Case study: SAPien community	Leimeister et al. (2009)
	Field study: 3 platforms	Geri et al. (2017)
Enjoyment	Case study: Istockphoto	Brabham (2008)
	Field study: Mechanical turk (ranking of motivations)	Kaufman et al. (2011)
	Field study: TaskCN	Sun et al. (2011, 2012) and Zheng et al. (2011)
Work autonomy	Case study: Threadless	Brabham (2010)
	Field study: Mechanical turk (ranking of motivations)	Kaufman et al. (2011)
	Field study: TaskCN	Zheng et al. (2011)
	Field study: Mechanical turk (narrative analysis)	Deng et al. (2016)

Trust in the crowdsourcing platform

There exist two main streams of literature studying trust in technology, i.e., interpersonal trust and system-like trust (Lankton et al., 2015). Since crowdsourcing platforms show a high degree of humanness, e.g., volition in solution evaluation and rewarding (Feller et al., 2012), as per Lankton et al. (2015), human-like trust in technology appears more appropriate for our context. Here, trust in the platform implies that the solver trusts that the platform will ensure fair evaluation and reward for his/her solution i.e., the platform acts as intermediary between the solver and other solvers or crowdsourcing firms. We thus define trust as a solver's implicit set of beliefs that the crowdsourcing platform will fairly evaluate solvers' solution and reward them for their work.

Past literature posits that trust matters in the face of risks and prevailing vulnerabilities (Jarvenpaa et al., forthcoming) and helps facilitate future behaviors (e.g., Kim, 2014). Trust is considered a relevant factor given the risks and vulnerabilities inherent in online activities (Jarvenpaa et al., forthcoming). In the context of crowdsourcing, risk concerns regarding seeker firms' opportunistic behaviors through the platform prevail (Afuah and Tucci, 2012). Thus, trust is an important factor that may affect solver participation in our study. Also, past crowdsourcing literature suggests that trust is critical for the success of crowdsourcing and may affect solvers' participation (Feller et al., 2012). However, there is a lack of research that has modeled and empirically tested its impacts. As trust reduces the need to act in a self-protective way and facilitates risk-taking behavior (Jarvenpaa et al., 1998), we posit that trust in the crowdsourcing platform will encourage solvers to participate in crowdsourcing in the face of potential risks and opportunistic behaviors.

Several studies have explored the antecedents of trust in online activities (e.g., Ridings et al., 2002; Porter and Donthu, 2008). Jarvenpaa et al. (forthcoming) review prior literature and find that structural assurances (e.g., 3rd party certificates, privacy protection, and escrow services) are important antecedents of trust in e-commerce. Porter and Donthu (2008) find that perceived effort to provide quality content and to foster member embeddedness (e.g., seek opinions of the members) help build trust in firm-sponsored virtual communities. In the context of crowdsourcing, past literature suggests that assuring solvers of being rewarded properly (Feller et al., 2012) and mitigating the costs of participation (Yang et al., 2008) should influence trust in the crowdsourcing platform. Hence, we posit that monetary reward, loss of knowledge power, and cognitive effort will affect trust. Based on the above arguments, we empirically examine the antecedents and consequence of trust in the context of crowdsourcing.

Research model and hypotheses

Drawing on social exchange theory and the context-related literature described above, we develop a model to explain solvers' participation behavior in crowdsourcing as shown in Fig. 1. We propose that monetary reward, skill enhancement, peer reputation, enjoyment, work autonomy and trust in the crowdsourcing platform will enhance solvers' participation in crowdsourcing, while cognitive effort and loss of knowledge power will inhibit their participation. We also propose that monetary reward, cognitive effort, and loss of knowledge power impact trust in the crowdsourcing platform.

Monetary reward

In competition-based crowdsourcing, monetary reward is typically provided as an incentive for solvers (Howe, 2008) i.e., solvers can expect to receive such reward from firms if their solutions are selected (Kaufman et al., 2011). Previous literature suggests that extrinsic motivations such as monetary reward are important drivers for individuals to undertake an action (e.g., Brabham, 2008, 2010; Zheng et al., 2011). For example, Terwiesch and Xu's (2008) analytic study suggests that monetary rewards will stimulate solvers' participation in crowdsourcing. In crowdsourcing platforms such as TaskCN, solvers may expect to receive money from seekers if their solutions are chosen (Sun et al., 2012). As per social exchange theory, expectation of monetary reward should motivate individuals to choose to act (Molm, 1997; Wasko and Faraj, 2005). Following the discussion above, we propose that expectation of monetary reward will enhance solvers' participation in crowdsourcing.

H1a. Monetary reward is positively related to solvers' participation in crowdsourcing.

It is recognized that the sustainability of a crowdsourcing platform is dependent on successful solvers being rewarded properly (Geri et al., 2017; Feller et al., 2012). Monetary reward is arguably the most important reward in crowdsourcing (Sun et al., 2012). As argued above, expectation of monetary rewards should increase future solver participation. Indeed, the likelihood of getting a monetary reward may heighten the perception of the reliability of a platform (Kankanhalli et al., 2015), and thereby enhance solvers' trust in the efficacy and fairness of the crowdsourcing process. Thus, solvers will believe that the crowdsourcing platform will ensure that their solution is properly rewarded if it is adopted (Feller et al., 2012). Conversely, a low expectation of monetary reward can lead solvers to focus on the potential loss and decrease their perception that the platform will fairly reward their effort. Hence, solvers will show a low trust in the crowdsourcing platform if so.

H1b. Monetary reward is positively related to solvers' trust in the crowdsourcing platform.

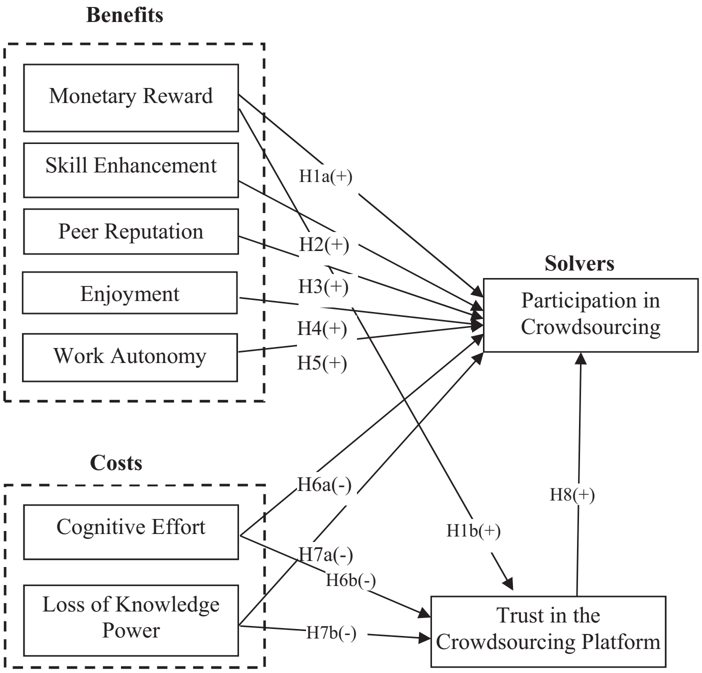

Fig. 1. Research model for solvers' participation.

Skill enhancement

Skill enhancement refers to the degree to which solvers expect to enhance their expertise through receiving feedback from the crowdsourcing process or by learning from others' solutions. Previous research has suggested that to avoid wasting effort, solvers will select problems that they think will add to their knowledge and benefit them in the future (Nov et al., 2010; Stewart and Gosain, 2006). In the context of this study, solvers are likely to participate in crowdsourcing if they think they can improve their skills or expertise through the process. Moreover, when solvers propose solutions, the staff members in the crowdsourcing platform or firms may provide feedback so that solvers can identify where their solutions fall short and what should be improved (Boons et al., 2015; Sieg et al., 2010). Such feedback provides guidance for solvers to improve their proposed solutions and enhance their skills in particular areas (Leimeister et al., 2009; Nov et al., 2010).

Consistent with the above reasoning, Brabham (2008) noted that some people are motivated to participate in iStockphoto[1] by the opportunity to learn new photography skills. In Brabham's (2010) case study of Threadless,[2] the opportunity to develop T-shirt design skills was found to be a factor that motivated individuals to submit designs. For photo-sharing website Flickr, Nov et al. (2010) noted that self-development is positively related to individual participation. In the context of our study, solvers may be able to learn or improve skills, such as marketing their solutions to firms, communication, logo or product outlook design, programming, and writing. Such learning opportunities could motivate solvers to participate. Thus, we expect that

H2. Skill enhancement is positively related to solvers' participation in crowdsourcing.

Peer reputation

Social exchange theory posits that individuals will be motivated to undertake an action if they can receive social rewards such as approvals, status, and respect from it (Blau, 1964). In the context of crowdsourcing, such social rewards can be derived from peers (other solvers) in the form of enhanced reputation (Leimeister et al., 2009; Nov et al., 2010) where peers respect and acknowledge solvers' skills and contributions to the platform. Peer reputation is an indicator of status in a community and fulfills fundamental human needs (Constant et al., 1994). Thus, peer reputation should motivate solvers to participate in crowdsourcing. For example, in their case study of the SAPien community, Leimeister et al. (2009) found that individuals' need for peer appreciation and acknowledgement of their knowledge is a motivator for their participation in crowdsourcing. A similar finding has been reported in Brabham's (2008) case study of iStockphoto and Geri et al.'s (2017) field study of a programmer Q&A website.

[1] http://www.istockphoto.com/.
[2] http://www.threadless.com/.

In the context of our study, successful solvers are interviewed by TaskCN to share their winning experience and their suggestions for other solvers. These interviews are shown on the winning solver webpage[3] of TaskCN. For each task, the winning solution is publicized for one week. Further, there are forums in TaskCN in which solvers interact with each other. Through these means, successful solvers become known to their peers. Following the reasoning above, we expect that peer reputation motivates solvers to participate in crowdsourcing.

H3. Peer reputation is positively related to solvers' participation in crowdsourcing.

Enjoyment

In general, individuals will undertake tasks if they enjoy solving them (Agarwal and Karahanna, 2000). Prior research suggests that solvers may be motivated by the enjoyment of taking up new or interesting tasks (Goh et al., 2017; Nov et al., 2010; Zheng et al., 2011). The crowdsourced tasks can arouse their interest and curiosity to explore new fields. The more enjoyment they perceive, the more likely they are to participate in future crowdsourcing. In Sun et al.'s (2011) study, hedonic value (enjoyment) is found to positively affect solvers' continuance intention to participate in crowdsourcing. Zheng et al. (2011) and Sun et al. (2012) also noted that enjoyment (part of intrinsic motivation) enhances solvers' intention to participate in crowdsourcing. Thus, we hypothesize

H4. Enjoyment is positively related to solvers' participation in crowdsourcing.

Work autonomy

Work autonomy refers to the degree to which the work provides freedom, independence, and discretion in determining what to do and the procedures to be used in carrying it out (Hackman and Oldham, 1975). Prior studies have found that work autonomy influences employees' perceptions of their ability to initiate, perform, and complete tasks (Xie and Johns, 1995) and their performance (Haas, 2010).

In the context of this study, crowdsourcing can allow solvers autonomy in deciding which tasks to solve and how to solve them (Kaufman et al., 2011). The benefit of work autonomy should motivate them to participate in crowdsourcing. For example, Deng et al.'s (2016) narrative analysis found that crowd workers (solvers) value autonomy in the crowdsourcing platform. Brabham's (2010) case study found that the potential to take up freelance work is one of the reasons for solvers to participate in Threadless. Zheng et al. (2011) also made similar observations regarding TaskCN. Hence, we hypothesize

H5. Work autonomy is positively related to solvers' participation in crowdsourcing.

Cognitive effort

Cognitive effort refers to the effort required for problem solving on crowdsourcing platforms, bridging the gaps between the context of past solutions or knowledge and that of current problems. Psychologists have noted that humans have limited cognitive resources (Garbarino and Edell, 1997; Russo and Dosher, 1983). Cognitive effort is costly, and as per social exchange theory (Molm, 1997), humans try to conserve their efforts. In the context of crowdsourcing, solvers need to exert cognitive effort to understand the task requirements, generate ideas, and come up with solutions (Boudreau and Lakhani, 2009). In general, to solve crowdsourced tasks, they would need cognitive effort to connect their expertise with proposed problems and develop solutions for them. Solvers are not likely to participate in crowdsourcing if they perceive that high cognitive effort is required for participation. Thus, we expect

H6a. Cognitive effort is negatively related to solvers' participation in crowdsourcing.

Solvers may expect the crowdsourcing platform to help reduce their cognitive effort, which can build their trust in the platform. For instance, crowdsourcing platforms can provide winning submissions as examples for other solvers (Ye and Kankanhalli, 2013) and offer feedback to solvers if their submissions are not adopted (Boons et al., 2015; Ye and Kankanhalli, 2015). Providing past solution examples could help reduce the cognitive effort needed and thereby facilitate solvers to formulate their solutions more easily (Yang et al., 2008). Also, platform functionalities supporting seeker-solver interactions and communications (e.g., feedback seeking) can help reduce the risk of potential disputes and misunderstanding (Deng et al., 2016). This can alleviate solvers' cognitive effort needed for problem solving, which can help enhance their trust in the platform.

If high cognitive effort is perceived, this may heighten solvers' belief that the crowdsourcing platform is not helpful in facilitating their participation and lead them to lower their trust in the platform. Conversely, when less cognitive effort is

[3] http://news.taskcn.com/gongzuozhefangwenxinde/8053.html.

seen to be needed for completing crowdsourcing tasks, solvers would believe that crowdsourcing platforms are helpful in supporting their participation and thus, they will place a higher trust in the platform. Therefore, we hypothesize

H6b. Cognitive effort is negatively related to solvers' trust in the crowdsourcing platform.

Loss of knowledge power

Loss of knowledge power refers to the loss of proprietary knowledge and the sole claim to the benefits stemming from such knowledge (Kankanhalli et al., 2005). In the knowledge management literature, the loss of knowledge power is reported as a barrier to knowledge sharing (Davenport and Prusak, 1998). By sharing a part of their unique knowledge, knowledge contributors give up sole claim to the benefits stemming from such knowledge (Gray, 2001; Kankanhalli et al., 2005). This cost may discourage individuals to share their knowledge. In the context of crowdsourcing, knowledge can be perceived as a source of power by solvers. They may fear losing their power or value if firms and peers come to know of their ideas prior to being rewarded (Afuah and Tucci, 2012). As per social exchange theory, this may result in potential solvers not taking part in the exchange, e.g., not participating in crowdsourcing. Hence, we expect

H7a. Loss of knowledge power is negatively related to solvers' participation in crowdsourcing.

Crowdsourcing platforms require solvers to reveal their proposed solutions for evaluation (Ye and Kankanhalli, 2015), resulting in a potential loss of knowledge power. Crowdsourcing firms may act opportunistically and not pay solvers once solutions are obtained (Afuah and Tucci, 2012). Solvers may believe that the crowdsourcing platform will misuse their submissions and take advantage of information asymmetries for its own benefits. As a result, this would decrease solvers' trust in the crowdsourcing platform. Further, uncertainties exist in evaluating the quality of solutions (Ye and Kankanhalli, 2015). Even if crowdsourcing firms are not opportunistic, not winning may also cause solvers to think less of crowdsourcing platform's competence in fairly evaluating their submission and hence lower their trust in the platform. Similarly, previous literature suggests that the perception of loss of knowledge power may intensify solvers' belief in the opportunistic behavior of firms and platforms (Afuah and Tucci, 2012), which will decrease trust in the platform and community (Porter and Donthu, 2008). Accordingly, we hypothesize:

H7b. Loss of knowledge power is negatively related to solvers' trust in the crowdsourcing platform.

Trust

Past research in online settings suggests that trust reduces an individual's need to act in a self-protective manner with others (Porter and Donthu, 2008), facilitates risk-taking behaviors (Jarvenpaa et al., 1998) and contributes to ongoing exchanges (Jarvenpaa et al., forthcoming), e.g., ongoing crowdsourcing participation. In the context of this study, when solvers trust that the crowdsourcing platform will protect their knowledge, they believe that the platform will reward them fairly and would not misuse their solutions (Feller et al., 2012). Hence, they will increase their participation. In contrast, low trust reflects the belief that solvers' efforts will not be fairly rewarded and the crowdsourcing firms and platforms may take advantage of solvers for their own benefits. As a result, solvers will decrease their participation.

H8. Trust in the crowdsourcing platform is positively related to solvers' participation in crowdsourcing.

Research methodology

Survey methodology was used to test our research model. To eliminate common method variance caused by a single data source (Podsakoff et al., 2003), we employed a survey to collect the independent variables, but used archival data from the platform for the dependent variable (actual solver participation behavior in crowdsourcing). Also, to better assess causality (Neuman, 2005), we collected archival data for the dependent variable three months after the survey for the independent variables. This ensures that the independent variables temporally precede the dependent variable.

Instrument development and conceptual validation

Since several constructs were adapted to the study context, we conducted a systematic procedure of instrument development (DeVellis, 2003) i.e., item creation and scale development, conceptual validation, and instrument testing. As far as possible, we adapted existing scales to our study context. Other than that, new items were developed as per the construct definitions shown in Table 3 or through interviews with solvers. Next, items for each construct were conceptually validated through unlabeled and labeled sorting exercises. In each exercise, two sets of four judges were used. The inter-judge agreement (i.e., Cohen's Kappa and agreement level) and item placement hit ratio were used to assess the conceptual reliability

Table 3
Definitions of constructs in the proposed model.

Constructs	Definition	Source
Monetary reward	The degree to which solvers expect that they will receive monetary incentives for their solutions proposed	Adapted from Bock et al. (2005)
Skill enhancement	The possibility of enhancing skills or expertise through receiving feedback from task solving on the crowdsourcing platform or learning from peers' solutions	Adapted from Lakhani and Wolf (2005)
Peer reputation	The perception of the increase in reputation among peers due to participation in crowdsourcing tasks	Adapted from Wasko and Faraj (2005)
Enjoyment	The perception of pleasure obtained from solving tasks on the crowdsourcing platform	Adapted from Nov et al. (2010)
Work autonomy	The degree to which the work provides substantial freedom and discretion in determining the choice of task type and the procedures to be used in carrying it out	Hackman and Oldham (1975) and Ahuja et al. (2006)
Cognitive effort	The efforts required for solvers to link their expertise with firms' problems and formulate their solutions	Adapted from Garbarino and Edell (1997)
Loss of knowledge power	The perception of power and unique value lost due to submitting solutions to tasks on the crowdsourcing platform that others may see or copy	Adapted from Gray (2001)
Trust in the crowdsourcing platform	The belief in the good intent, competence, and reliability of the crowdsourcing platform with respect to solution evaluation and reward	Adapted from Putnam (1993)
Solvers' participation in crowdsourcing	The number of tasks solvers have participated in a given time period	Adapted from Zheng et al. (2011)

and validity of the instrument. Our analysis shows that in both rounds of item sorting, the Kappa score agreement level and hit ratios for all items were greater than 0.8, suggesting sufficient item reliability and validity (Jarvenpaa et al., 1998). Last, the validated items were combined together into the overall questionnaire and tested in a pilot study, which will be described next.

Pilot study

A pilot study was conducted to assess the reliability and validity and to identify any potential problems with the instrument, as indicated by the respondents. We pilot tested the instrument in zhubajie.com, a crowdsourcing platform similar to, but smaller than TaskCN that was used for our main study. To pilot test the instrument, we surveyed 106 solvers in zhubajie.com. Based on the pilot test results, one item each for *Monetary Reward* and *Skill Enhancement* were removed due to their low loadings. After removing these items, the exploratory factor analysis demonstrated sufficient instrument validity. We also edited item wordings in the instrument according to the feedback from the pilot test and follow-up interviews. The final instrument is shown in Table 4. All items were measured on 7 point Likert scales anchored from Strongly Disagree to Strongly Agree.

Data collection

Subsequently, we collected data from solvers in TaskCN.com to test the model. TaskCN is a third party platform founded in 2005 to host crowdsourcing tasks. It is considered as one of the most popular and established crowdsourcing websites in China. By the end of 2016, TaskCN hosted over 3.6 million registered solvers and over 61 thousand tasks.[4] This platform has been featured not only in the media, but also in IS research (e.g., Sun et al., 2012; Zheng et al., 2011). The selection of this platform allows us a sufficiently large pool of solvers to test our model. Furthermore, the existence of previous studies on this platform allows us to compare our results with prior work.

We invited solvers in TaskCN to participate in our survey by sending emails to them through the internal messaging tool. As a token of appreciation for their participation, a $10 voucher was given to each respondent. A total of 165 responses were received of which 156 valid responses remained after removing incomplete data. We used the survey instrument to measure the independent variables. For the dependent variable (solvers' participation in crowdsourcing), we collected data on the number of submissions by the solver in the three months after the survey. We tested for non-response bias by comparing early and late respondents (Armstrong and Overton, 1997). T-tests of the differences between the earliest 10% and the last 10% respondents in terms of demographics revealed no systematic differences. Thus, there is no evidence of non-response bias in this study.

Control variables

We also included demographic and background information of the solvers as control variables in our model. These variables include solvers' age, gender, education, tenure, past experience, and previous performance in the crowdsourcing platform. Past experience refers to the number of tasks that solvers have participated in before. Previous performance refers to the number of times solvers have won rewards on the platform in the past. Also, the status of solvers and type of tasks may affect their participation in crowdsourcing. Status of solvers refers to whether they are professionals (status 1) or amateurs

[4] www.taskcn.com.

Table 4
Items of constructs in the proposed model.

Constructs	Items	Source
Monetary reward	**MON1:** I expect to receive monetary rewards in return for my submission **MON2:** I expect to receive monetary rewards for my submission **MON3:** I will be financially rewarded by firms for my submission	Adapted from Bock et al. (2005)
Skill enhancement	**SKL1:** Participating in solving problems in the platform helps me improve my own skills in a particular area **SKL2:** I can enhance my skills in a particular area through participation **SKL3:** Solving tasks in the platform helps improve my skills in an area	Developed from Nov et al. (2010)
Peer reputation	**REP1:** I will earn respect from peers by winning the task in the platform **REP2:** I feel that winning the tasks improves my reputation among peers in the platform **REP3:** Winning rewards in the platform will improve my reputation among peers in the community **REP4:** Winning the tasks helps improve my image among peers	Kankanhalli et al. (2005) and Wasko and Faraj (2005)
Enjoyment	**ENJ1:** I enjoy solving novel tasks proposed in the platform **ENJ2:** The challenge of solving novel tasks proposed in the platform is enjoyable for me **ENJ3:** I feel good when solving the tasks from the platform **ENJ4:** I enjoy taking up the tasks from the platform	Kankanhalli et al. (2005) and Wasko and Faraj (2005)
Work autonomy	**AUT1:** I can select the type of tasks I work on in the platform **AUT2:** I have freedom to decide how I perform the chosen task in the platform **AUT3:** I can freely choose any approach to perform tasks in the platform **AUT4:** I have the authority to choose any task in the platform	Ahuja et al. (2006)
Cognitive effort	**COG1:** I try very hard to understand task requirements in the platform **COG2:** I need to put in effort into understanding firms' task requirements **COG3:** I need to input much time and effort to solve tasks in the platform **COG4:** I need to put in time into solving firms' problems	Developed from Petty et al. (1980) and Garbarino and Edell (1997)
Loss of knowledge power	**LOS1:** Providing my solutions through the platform makes me lose my unique value **LOS2:** Providing my solutions through the platform makes me lose my power base **LOS3:** Providing my solutions through the platform makes me lose my knowledge that makes me stand out with respect to others **LOS4:** Providing my solutions through the platform makes me lose my knowledge that no one else has	Adapted from Kankanhalli et al. (2005)
Trust in the crowdsourcing platform	**TRU1:** I believe that the platform gives credit for solvers' solutions **TRU2:** I believe that the platform will not misuse my solutions **TRU3:** I believe that the platform guarantees the rewards if solutions were adopted **TRU4:** I believe that the platform protects solvers' interests	Adapted from Kankanhalli et al. (2005)

(status 0). Professional solvers who mainly rely on TaskCN for their income may be more likely to actively participate in crowdsourcing than amateur solvers. The types of tasks were classified according to the TaskCN task categories and were included as dummy variables. Since the difficulty of each type of task differs, this may affect solvers participation in crowdsourcing (Ye and Kankanhalli, 2013). The respondent demographics and background are summarized in Table 5.

Data analysis and results

For the analysis, structural equation modeling (SEM) was chosen over linear regression, because SEM can simultaneously analyze all paths with latent variables in one analysis (Gefen et al., 2011). Within SEM, Partial Least Squares (PLS) was chosen over co-variance based SEM for two reasons. First, the dependent variable (i.e., solvers' participation in crowdsourcing) is measured with archival data, which may not conform to the proportionality constraints and uncorrelated measurement errors of co-variance based SEM (Gefen et al., 2011). Second, PLS is a suitable choice for a multi-stage model (Gefen et al., 2011; Wetzels et al., 2009). We used SmartPLS 2.0 to analyze the data.

Instrument validity

To validate our survey instrument, convergent and discriminant validity tests were conducted (Hair et al., 2009). Convergent validity was assessed by examining the Cronbach's α (CA) (>0.7), composite reliability (>0.7), average extracted variance (AVE) (>0.5), and factor analysis results (Straub et al., 2004). Table 6 shows that the values of CA, CR, and AVE for each model construct (all are reflective) satisfy the thresholds. Also, the factor loadings of each item on the intended

Table 5
Respondents' background.

Control variables		Frequency (N = 156)	Percentage (%)	Control variables		Frequency (N = 156)	Percentage (%)
Gender	Male	106	67.95	Status	Amateur	122	78.21
	Female	50	32.05		Professional	34	21.79
Age	16–20	19	12.18	Task type	Website design and programming	15	9.62
	21–25	87	55.77		Logo, benchmark, and product outlook design	49	31.41
	26–30	29	18.59		Writing and translation	47	30.13
	31–35	12	7.69		Laborious tasks (e.g., Post Ads in communities)	27	17.31
	36–40	5	3.21		Others	18	11.54
	>40	4	2.56	Previous performance	0	97	62.18
Education level	High school	18	11.54		1–3	26	16.67
	Bachelors	124	79.49		4–6	19	12.18
	Masters	9	5.77		>6	14	8.97
	Doctorate	5	3.21	Past experience	0	9	5.77
Tenure (Months)	3–6	19	12.18		1–5	74	47.43
	7–9	34	21.79		6–10	53	33.97
	10–12	22	14.10		>10	20	25.64
	>12	81	51.92				

Table 6
Descriptive statistics and convergent validity.

Construct	Min	Max	Mean	STD	AVE	CR	CA
Work Autonomy (AUT)	1	7	5.71	1.30	0.79	0.94	0.91
Monetary Reward (MON)	3.67	7	6.07	1.29	0.78	0.91	0.86
Skill Enhancement (SKL)	2	7	5.53	1.56	0.78	0.92	0.86
Enjoyment (ENJ)	2.5	7	5.57	1.37	0.59	0.85	0.77
Peer Reputation (REP)	1	7	4.91	1.72	0.70	0.90	0.86
Cognitive Effort (COG)	1	7	5.37	1.49	0.76	0.93	0.90
Loss of Knowledge Power (LOS)	1	7	2.89	1.77	0.74	0.92	0.93
Trust (TRU)	1.75	7	5.05	1.51	0.71	0.91	0.88
Solvers' participation[a]	0	64	7.25	13.32	–	–	–

[a] Single item construct measured by number of tasks participated within three months.

construct were larger than 0.7 (see Table 7). All the criteria are satisfied, suggesting sufficient convergent validity of the model constructs (Straub et al., 2004).

Discriminant validity was assessed by examining the indicator-factor loadings and comparing the construct AVEs with inter-construct correlations (Gefen and Straub, 2005). The results in Table 7 show that all indicators load more strongly on their corresponding constructs than on other constructs in the model and the item loadings on unintended constructs were lower than 0.4. The results in Table 8 also show that the square root of AVE is larger than the corresponding inter-construct correlations. Thus, the model constructs demonstrate sufficient discriminant validity. Also, we did not observe high correlations among predictors in the table, indicating the absence of multicollinearity.

Since we collected data for our independent variables and dependent variable from two independent sources, common method variance (CMV) should not be an issue in our study (Podsakoff et al., 2003). Nevertheless, Harman's single factor test was conducted by running an exploratory factor analysis with all variables included (Podsakoff et al., 2003). The factor analyses produced neither a single factor nor one general factor that accounted for the majority of the variance (>50%). This suggests that common method bias is not a problem in this study.

Results of hypotheses testing

We tested our hypotheses using PLS-SEM with bootstrapping of 5000 samples (Hair et al., 2009). Table 9 shows the hypothesis testing results. The model explains 45% of the variance in solvers' participation in crowdsourcing. As the results in Table 9 show, among the control variables, previous performance and status are significantly related to solvers' participation in crowdsourcing. This suggests that professional solvers and those who performed better in the past tend to be more active participants.

As hypothesized, monetary reward, skill enhancement, enjoyment, work autonomy, and trust were positively related to solvers' participation in crowdsourcing (H1a, H2, H4, H5 and H8 are supported), while cognitive effort was negatively related

Table 7
Exploratory factor analysis results.

	1	2	3	4	5	6	7	8
AUT1	0.09	−0.01	0.11	−0.01	0.11	**0.90**	0.08	−0.09
AUT2	0.08	−0.09	−0.03	0.06	0.15	**0.89**	0.04	0.04
AUT3	0.13	−0.11	0.07	−0.03	0.10	**0.93**	0.15	0.09
AUT4	0.06	0.00	0.16	0.02	0.10	**0.87**	0.17	−0.17
MON1	−0.06	−0.05	0.12	0.17	−0.06	−0.16	0.14	**0.91**
MON2	0.00	−0.05	0.07	0.07	0.11	0.06	−0.05	**0.90**
MON3	0.04	0.11	0.22	0.20	0.16	−0.04	0.12	**0.84**
SKL1	0.20	−0.16	0.09	−0.01	**0.88**	0.15	−0.04	0.07
SKL2	0.30	−0.03	0.07	−0.02	**0.90**	0.10	0.04	−0.01
SKL3	0.12	0.02	0.04	0.04	**0.85**	0.17	0.31	0.10
ENJ1	0.06	−0.02	0.13	0.18	0.11	0.08	**0.75**	0.01
ENJ2	0.15	−0.01	0.12	−0.08	0.16	0.08	**0.75**	0.04
ENJ3	0.36	−0.15	0.09	0.13	0.17	0.23	**0.74**	0.13
ENJ4	0.30	−0.05	−0.06	0.04	0.12	0.24	**0.82**	0.08
REP1	0.15	0.09	**0.87**	0.02	0.02	0.08	0.16	0.11
REP2	0.09	−0.02	**0.76**	0.19	0.25	0.03	0.03	0.04
REP3	0.18	0.06	**0.81**	0.03	0.05	0.08	0.07	0.07
REP4	0.06	0.09	**0.89**	0.04	0.02	0.11	0.04	0.19
COG1	0.06	0.08	−0.08	**0.84**	−0.02	0.09	−0.09	0.08
COG2	0.01	0.09	0.12	**0.93**	−0.10	−0.02	−0.01	0.02
COG3	0.00	0.04	0.11	**0.84**	0.24	0.01	0.15	0.11
COG4	0.00	0.07	0.10	**0.88**	0.00	−0.04	0.15	0.20
LOS1	0.01	**0.94**	0.01	0.06	−0.16	−0.03	−0.02	−0.07
LOS2	0.00	**0.84**	−0.02	0.05	−0.06	−0.05	0.02	−0.04
LOS3	−0.19	**0.91**	0.17	0.05	0.06	−0.10	−0.09	0.02
LOS4	−0.16	**0.75**	0.06	0.12	0.03	−0.03	−0.06	0.10
TRU1	**0.84**	0.00	0.04	0.10	0.18	0.14	0.21	0.04
TRU2	**0.90**	−0.10	0.19	0.02	0.18	0.06	0.20	−0.01
TRU3	**0.87**	−0.13	0.14	−0.02	0.06	0.08	0.02	−0.03
TRU4	**0.90**	−0.10	0.10	−0.02	0.07	0.07	0.12	−0.03
Eigenvalue	9.32	4.15	3.42	2.16	1.81	1.56	1.44	1.29
% of variance	25.88	11.54	9.49	7.99	6.01	5.33	5.00	4.03
Cumulative%	25.88	37.42	46.91	54.90	60.91	66.24	71.24	75.27

Table 8
Correlations.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. AUT	0.90															
2. MON	0.25	0.88														
3. SKL	0.42	0.52	0.88													
4. ENJ	0.41	0.32	0.28	0.76												
5. REP	0.30	0.18	0.18	0.36	0.84											
6. COG	−0.08	0.07	−0.11	0.10	0.16	0.87										
7. LOS	−0.14	−0.12	−0.05	−0.20	0.14	0.16	0.86									
8. TRU	0.07	0.21	0.09	0.35	−0.09	0.06	−0.13	0.88								
9. Solvers' participation	0.45	0.24	0.27	0.38	0.16	−0.22	−0.20	0.35	[a]							
10. Tenure	0.04	−0.10	−0.08	0.02	0.02	−0.04	0.08	−0.22	0.22	[a]						
11. Gender	0.08	−0.13	−0.01	0.11	0.07	0.13	0.08	−0.04	0.10	0.10	[a]					
12. Age	0.09	0.10	0.00	0.10	0.07	0.22	0.09	−0.11	0.09	0.26	0.09	[a]				
13. Education	0.11	0.10	0.01	0.12	−0.05	0.08	0.09	−0.25	0.07	0.16	0.06	0.16	[a]			
14. Status	0.10	0.21	0.07	0.13	0.09	0.13	0.01	0.04	0.13	0.09	−0.12	0.13	0.09	[a]		
15. Previous performance	0.12	0.01	0.01	0.19	0.01	−0.05	−0.12	0.06	0.28	0.01	0.07	0.09	0.17	0.21	[a]	
16. Past experience	0.13	0.10	0.20	0.07	0.12	0.02	0.01	0.11	0.09	0.20	0.01	0.12	0.11	0.21	0.43	[a]

Notes
\+ Diagonal elements are the square root of average variance extracted (AVE).
– Dummy variables are not included in the correlation table, i.e., task type.
[a] Excluded because construct has a single measure.

to the DV (H6a is supported). In addition, consistent with our hypotheses, monetary reward was positively related to trust, while loss of knowledge power negatively affected trust (H1b and H7b are supported). However, contrary to our hypotheses, peer reputation and loss of knowledge power were not related to solvers' participation in crowdsourcing, while cognitive effort was not related to trust (H3, H6b, and H7a are not supported).

Table 9
Results of hypotheses testing.

	DV = Solvers' participation			DV = Trust	
	1	2	Result	3	Result
Age	0.04	0.09	N.S.		
Gender	−0.06	−0.02	N.S.		
Education level	−0.07	−0.04	N.S.		
Tenure	0.06	0.05	N.S.		
Status	0.15*	0.10*	Sig.		
<u>Task type (baseline others)</u>					
Website design and programming	0.03	0.01	N.S.		
Logo design	0.04	0.02	N.S.		
Writing and translation	0.03	0.05	N.S.		
Laborious tasks	−0.12	−0.02	N.S.		
Previous performance	0.27*	0.20*	Sig.		
Past experience	0.02	0.05	N.S.		
Monetary reward		0.17**	**H1a supported**	0.16*	**H1b supported**
Skill enhancement		0.13*	**H2 supported**		
Peer reputation		−0.01	H3 not supported		
Enjoyment		0.11*	**H4 supported**		
Work autonomy		0.23**	**H5 supported**		
Cognitive effort		−0.21*	**H6a supported**	0.08	H6b not supported
Loss of knowledge power		−0.07	H7a not supported	−0.15*	**H7b supported**
Trust		0.14*	**H8 supported**		
R^2	0.16	0.45		0.08	
Observations	156				

*** $p < 0.001$.
* $p < 0.05$.
** $p < 0.01$.

Table 10
Post-hoc comparison.

		MON → DV	SKL → DV	REP → DV	ENJ → DV	AUT → DV	TRU → DV	COG → DV	LOS → DV
Path coefficient (Standard error)	Professional	0.30 (0.132)	0.11 (0.099)	−0.06 (0.081)	0.15 (0.112)	0.08 (0.091)	0.47 (0.134)	−0.14 (0.079)	−0.07 (0.065)
	Amateur	0.26 (0.165)	0.12 (0.093)	−0.04 (0.079)	0.14 (0.110)	0.51 (0.115)	−0.01 (0.076)	−0.09 (0.081)	−0.06 (0.067)
S_{pooled}		0.147	0.097	0.080	0.111	**0.102**	**0.049**	**0.079**	0.065
T-test across groups		1.67	−0.64	−1.53	0.55	**−26.04*** **	**60.33*** **	**−3.86*** **	−0.935

*** $p < 0.001$.

Post hoc tests

To obtain a more comprehensive view of the phenomenon and enrich our understanding (Venkatesh et al., 2013), we post hoc tested for the mediating effect of trust. Following Baron and Kenny's (1986) steps, we also conducted the Sobel test to detect the mediating effect. Since loss of knowledge power had no significant effect on the DV and cognitive effort had no significant effect on trust, we only tested the mediating effect of trust on the relationship between monetary reward and solver participation. We found that trust partially mediates the relationship between monetary reward and solver participation (T value = 2.45, $p < 0.05$).

Further, since professional solvers may perceive trust, benefit, and cost factors differently from amateur solvers, we also post hoc tested the model separately for professional vs. amateur solvers. There were 122 amateur solvers and 34 professional solvers in our sample. Following the procedure described in Keil et al. (2000), we divided the sample into the two groups and compared the importance of each factor. The results in Table 10 show that professional solvers pay more attention to trust and cognitive effort while amateur solvers place more importance on work autonomy. No significant differences were found in the importance of monetary reward, skill enhancement, peer reputation, enjoyment, and loss of knowledge power between professional and amateur solvers.

Discussion

To succeed in creating value for firms, crowdsourcing platforms should maintain a significant pool of skilled solvers for organizational tasks. It is however, challenging for crowdsourcing platforms to publicize themselves and establish a network of talented solvers. Therefore, researchers and practitioners are interested to understand how to encourage solvers' participation in crowdsourcing (Afuah and Tucci, 2012; Majchrzak and Malhotra, 2013). Based on social exchange theory and context-related literature, we developed and tested a model to explain solvers' participation in crowdsourcing. Our study found that monetary reward, skill enhancement, enjoyment, work autonomy, trust, and cognitive effort are significantly related to solvers' participation in crowdsourcing. Also, monetary reward was positively related, and loss of knowledge power negatively related to trust.

Contrary to our prediction, peer reputation was not related to solvers' participation in crowdsourcing. To understand why this relationship was not significant, following the guidelines from Venkatesh et al. (2013), we interviewed three successful solvers in TaskCN. They pointed out that peer reputation may not be desired, as peers are perceived as competitors on the platform. Peers learn from others' successful solutions. Thus, a higher peer reputation may attract others to imitate the solver's work.

Additionally, loss of knowledge power was not related to solvers' participation in crowdsourcing, but was related to trust. High loss of knowledge power resulted in low trust in the platform, and thereby low participation in crowdsourcing. Thus, loss of knowledge did not directly affect solver participation, but did so indirectly through trust. This result can be explained by the presence of plagiarism detection mechanisms in TaskCN (Yang et al., 2008). These mechanisms reduce solvers' perceptions of the loss of knowledge power in TaskCN and thus solvers tend to trust the platform more. Regarding the insignificant relationship observed between cognitive effort and trust, this could happen when cognitive effort is perceived more as a personally determined factor (Garbarino and Edell, 1997) rather than being related to the external environment – in this case, the crowdsourcing platform. As a result, it may not affect trust.

Limitations and future research

The findings of this study should be interpreted in light of its limitations. First, our study focuses on one type of crowdsourcing platform i.e., a financially rewarded competition-based and third party hosted crowdsourcing platform. Future research could explore other crowdsourcing platforms to test if the results of this study hold. For example, the model could be tested in collaboration-based voluntary crowdsourcing platforms such as Wikipedia. Also, future research can examine crowdsourcing platforms for complex tasks. For example, in platforms like InnoCentive, complex tasks require considerable effort and solvers' specialized knowledge for task solving. This may change solvers' perceptions of certain costs and benefits of participation, such as enjoyment and cognitive effort.

Second, while we studied the influences of perceived costs and benefits on solvers' participation in crowdsourcing, future work can explore the process of task solving and solvers' performance outcomes in crowdsourcing. For instance, researchers can investigate the factors that influence the process of task solving and as a result impact performance in crowdsourcing. Future research could investigate how crowdsourcing platforms and IT artefacts can facilitate solvers' participation in crowdsourcing (Cui et al., 2015). Furthermore, we measured general trust towards the platform. There are different kinds of trusting beliefs (e.g., competence, benevolence and integrity), which could have distinct impacts (McKnight et al., 2002). Future research could study the impact of the separate trusting beliefs. In addition, future studies can compare the importance of costs and benefits in driving solver participation, i.e., the different weighting of benefit and cost factors.

Third, this study explored the influences of costs and benefits on solvers' participation, based on social exchange theory and context-related literature. Future research could examine other determinants of solvers' participation in crowdsourcing. For example, researchers can explore the effects of external environmental conditions (e.g., anonymity) (Feng and Ye, 2016) on solvers' participation in crowdsourcing. Additionally, studies can examine the influences of network structures between individual solvers on their participation in crowdsourcing.

Theoretical contributions

This study offers several important contributions by modeling the influences of trust and both benefit and cost factors on solvers' actual participation in crowdsourcing. First, we add to the literature by developing a comprehensive model to explain the antecedents of solvers' *actual* participation in crowdsourcing and empirically validating it using survey and archival data. Our findings suggest that the antecedents of solvers' participation in crowdsourcing may differ from those of the intention to participate, i.e., peer reputation significantly drives solvers' intention to participate in crowdsourcing (cf. Zheng et al., 2011) but not their actual participation, while cognitive effort inhibits their participation. The reasons behind the differences require further investigation.

Second, this paper draws on the knowledge management literature, but also differentiates from it. Unlike knowledge sharing in previously studied contexts, crowdsourcing has sometimes been taken on by freelancers as a way to increase their income and improve their skills (Kaufman et al., 2011; Ye and Kankanhalli, 2013). Here, monetary reward, work autonomy, and skill enhancement are identified as important contextual factors that motivate solvers to participate in crowdsourcing. Thus, this paper contributes to the literature by identifying and empirically validating unique contextual motivators for crowdsourcing participation.

Third, previous studies mainly examined the influences of benefit factors on solvers' intention to participate in crowdsourcing (e.g., Sun et al., 2012; Zheng et al., 2011), while the cost antecedents have rarely been explored. Our study examined the cost antecedents and found that cognitive effort negatively relates to solvers' participation in crowdsourcing. In this way, we contribute to the literature (e.g., Boons et al., 2015; Geri et al., 2017; Deng et al., 2016; Sun et al., 2012; Zheng et al., 2011) by modeling and empirically testing the influences of cost factors i.e., cognitive effort, on solvers' participation in crowdsourcing. The findings enrich our understanding of solvers' participation in crowdsourcing by showing that cost factors should be considered when encouraging solvers' participation.

Fourth, we examined the role of trust in determining solvers' participation in crowdsourcing. As hypothesized, trust was positively related to solver participation in the context of crowdsourcing. This finding contributes to the crowdsourcing literature (e.g., Feller et al., 2012) by quantitatively validating its effects and to the trust literature by extending the application of trust in the context of crowdsourcing. Furthermore, we found that monetary reward and loss of knowledge power influence trust in the crowdsourcing platform. This result adds to the literature by identifying the cost and benefit antecedents of trust in the context of crowdsourcing. The finding of a mediating effect of trust also adds to prior literature on trust (e.g., Jarvenpaa et al., forthcoming; Porter and Donthu, 2008) by demonstrating that trust mediates the effect of monetary reward on solvers' participation in crowdsourcing.

Fifth, this study contributes to the literature on social exchange theory. Social exchange theory has mainly been applied to understand knowledge contribution in organizations (e.g., Kankanhalli et al., 2005) and online communities (e.g., Ye et al., 2015). Here, we extend the application of social exchange theory to explain solvers' participation in the context of crowdsourcing. Indeed, the explanatory power of the model indicates that social exchange theory is an appropriate lens to explain solvers' actual participation in crowdsourcing. Furthermore, this study adds to the social exchange literature by identifying new relationships, i.e., the impacts of monetary reward and loss of knowledge power on trust.

Last but not the least, our study contributes to the strategic IS literature on crowdsourcing (e.g., Majchrzak and Malhotra, 2013; Feller et al., 2012; McKnight et al., 2002; Ridings et al., 2002). It does so by explicating the drivers and inhibitors for solvers' participation in crowdsourcing, which is a prerequisite for seeker firms to benefit from crowdsourcing their tasks. In this way it suggests salient conditions needed for seeker organizations to be able to leverage this strategic business opportunity and thereby lower their innovation costs through access to external expertise.

Practical implications

From a pragmatic perspective, we offer insights to firms and crowdsourcing platform administrators on how to encourage solvers to participate in crowdsourcing. Specifically, this study contributes to practice in three ways.

First, it provides suggestions for encouraging solvers to participate in crowdsourcing through enhancing various benefits. Specifically, the results suggest that firms and crowdsourcing platforms should heighten the perceptions of monetary reward, enjoyment, skill enhancement, and work autonomy in order to promote solvers' participation in crowdsourcing. On the one hand, crowdsourcing platforms should create workable business models and monetization strategies to encourage solvers' participation in crowdsourcing. They should also reconsider their profit sharing policies. Currently, in TaskCN, the crowdsourcing platform retains 20% of the rewards for each task as its commission. Thus, TaskCN may reduce its commission fee to attract more solvers to participate in crowdsourcing. On the other hand, firms and crowdsourcing platforms can communicate the notion that participation in crowdsourcing is fun and enjoyable. For this purpose, platforms could create an experience-sharing webpage for solvers to broadcast their enjoyable and fun crowdsourcing experiences. Also, platforms could establish virtual reward systems (e.g., badges or points for collection) to enhance enjoyment in crowdsourcing (Goh et al., 2017). Additionally, they can highlight the work autonomy achievable in such platforms. This could be done by advertising to solvers that they have the autonomy to realize the value of their skills through crowdsourcing i.e., by freely choosing the type of tasks they want to solve and the methods for solving them. Last, platforms could communicate the message that solvers can improve their skills through participating in crowdsourcing contests. They could inform solvers that participation in crowdsourcing is an effective way for solvers to acquire and hone their skills in specific areas.

Second, crowdsourcing platforms could attempt to alleviate the costs for solvers to participate in crowdsourcing. To reduce cognitive effort, platforms could assist solvers to better understand seekers' problems and support them in proposing solutions. Further, platforms can work with seekers to better define problems in a way that can be clearly understood by solvers. Tools and mechanisms should also be provided to facilitate the communication between solvers and seekers so that task requirements can be better understood, hence reducing solvers' cognitive effort requirement.

Third, crowdsourcing platforms should note that solvers' trust promotes their participation in crowdsourcing and partially mediates the effect of monetary reward. Thus, it is important for the platform to cultivate trust in solvers. Specifically, they should take care in ensuring that solvers obtain appropriate rewards if their submissions have been adopted. They should also be reliable and keep their commitments to solvers. Last, we note that the crowdsourcing model has been challenging the understanding of traditional organizational boundaries, i.e., blurring the boundary between employees and non-employees (Geri et al., 2017; Kietzmann, 2017). In future, firms can better tap on crowdsourcing for their strategic initiatives, e.g., they can not only crowdsource tasks once performed by employees, but also use the crowd to work on innovative tasks that have never been considered before.

Conclusion

Solvers' participation in crowdsourcing platforms is critical to these platforms' survival and to achieving beneficial outcomes for seeker firms (e.g., Afuah and Tucci, 2012; Boons et al., 2015). To understand how to encourage solver participation, we have developed and tested a model based on social exchange theory and context-related literature to explain the influences of trust and both benefit and cost factors on solvers' actual participation behavior in crowdsourcing. Our findings indicate that monetary reward, skill enhancement, work autonomy, enjoyment, and trust positively influence solvers' actual participation in crowdsourcing, while cognitive effort deters solvers from participating in crowdsourcing. Further, we find that monetary reward positively influences, and loss of knowledge power negatively influences trust. These findings add to the growing body of research on crowdsourcing. They also provide suggestions for practitioners regarding what incentives should be provided, what costs should be reduced, and the role of trust in promoting solvers' participation in crowdsourcing.

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