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Investigating the antecedents of organizational task crowdsourcing

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ABSTRACT

Crowdsourcing is increasingly recognized as a potential approach to organizational task solving. However, few studies have explored and statistically tested the antecedents underlying the crowdsourcing intentions of organizations. This paper examines the antecedents of firms' crowdsourcing intentions based on transaction cost theory and the resource-based view and validates these antecedents using survey data from 161 organizations. The results indicated that the perceived benefits of cost reduction, brand visibility, and access to specialized skills positively affect firms' intention to crowdsource, while codification costs and proposal evaluation costs negatively influence firms' crowdsourcing intentions, both directly and indirectly, by diminishing perceptions of cost reduction.

1. Introduction

Crowdsourcing is a phenomenon in which an organization (i.e., seeker) recruits a large group of undefined individuals (i.e., solvers), referred to as the crowd, to work on organizational tasks via Internet-based platforms [44]. As these crowds become more connected and informed [71], they can contribute their distinct expertise to solve organizational problems [44,24]. Thus, firms are starting to leverage the wisdom of the crowd and realize the benefits of a crowdsourcing strategy [94].

This trend is evident in the emergence of crowdsourcing platforms, such as Amazon Mechanical Turk, InnoCentive, and TaskCN [50,88]. For example, Amazon Mechanical Turk hosts more than 100,000 tasks daily.[1] TaskCN is one of the largest crowdsourcing platforms in China for performing tasks such as website development, advertisement posting, and business proposal writing. Even established market leaders such as Google and Dell have recognized the potential of crowdsourcing. In 2008, Google funded a $10 million crowdsourcing project (Project 10^100) that called for ideas from the crowd to change the world [89]. Dell launched the IdeaStorm platform in 2007 to collect innovation ideas from the public [9]. As of September 2014, more than 548 ideas have been implemented.[2]

However, seeker firms encounter challenges in conducting crowdsourcing activities, including selecting the tasks to crowdsource and appropriately formulating these tasks to obtain satisfactory solutions. Ambiguously defined tasks can mislead solvers, resulting in the return of unsatisfactory solutions to seeker firms [2,21]. Crowdsourcing requires that the employees of a firm work with crowdsourcing platforms to specify task requirements, provide feedback for further improvement of solvers' proposals, and select final solutions [74]. For certain tasks, transferring specifications from seeker firms to solvers to allow the latter to provide solutions through crowdsourcing may be arduous [12]. These activities may incur costs for seekers (e.g., in terms of employee time and effort), in opposition to the purpose of crowdsourcing, i.e., lowering the cost of solving organizational tasks. Thus, there is a need to examine and understand the costs that firms may perceive when deciding to crowdsource tasks.

Prior research in this area [12,72] has primarily examined the factors that motivate firms to crowdsource tasks through conceptual or case studies. In a conceptual paper, Schenk and Guittard [72] proposed that crowdsourcing enables firms to mobilize external competencies for internal tasks at lower cost.

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[1] https://www.mturk.com/mturk/welcome.

[2] http://www.ideastorm.com/.

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A descriptive study of Mechanical Turk [52] suggested that crowdsourcing can be a less expensive way to solve firms' problems and a viable approach to obtain creative solutions. However, previous research on seekers' crowdsourcing behavior has consisted mainly of conceptual [12,72] or case studies [52,87] proposing the benefits of crowdsourcing for seekers. Thus, there is an absence of theoretically driven empirical research to explain the antecedents (including the costs) of seeker participation in crowdsourcing (for a thorough review, see [91]). These research gaps are the motivation for this study.

This paper aims to address this knowledge gap by developing a model to answer the following research question: *what drives (or inhibits) firms to crowdsource internal tasks?* Drawing on the resource-based view and transaction cost theory, a context-specific model was developed to explain seeker firms' intention to crowdsource. The model proposes perceived obtainable resources that enhance firms' intention to crowdsource and costs that reduce their intention to crowdsource. The model is tested using a field survey of 161 seeker firms in TaskCN, one of the largest crowdsourcing platforms in China. The results are expected to contribute to research and practice by further elucidating the determinants of a firm's intention to crowdsource internal tasks.

2. Conceptual background

This section reviews and identifies theories, i.e., the resource-based view and transaction cost theory, that could shed light on a firm's intention to crowdsource. Informed by these theories and the related literature, relevant constructs for the model are subsequently conceptualized.

Similarities have been noted between crowdsourcing and outsourcing [2,72]; both employ external talents to work on organizational tasks. For both strategies, the process of managing external parties and the final outcomes are subject to uncertainty. Given these similarities, the theories applied in the outsourcing literature could be applicable in the context of crowdsourcing [72]. Thus, we review theories employed in the outsourcing literature and examine their relevance to understanding crowdsourcing behavior. Three broad perspectives have been commonly used to explain the determinants of outsourcing: strategic, economic, and relational [41]. The strategic perspective concerns the strategies organizations formulate for outsourcing and how they allocate resources to pursue these strategies and obtain desirable performance. This perspective includes lenses such as the resource-based view [7], the knowledge-based view [33], resource-dependency theory [62], firm strategy theory [70], and game theory [83]. The economic perspective is related to the strategic view and considers how the benefits of outsourcing can be achieved efficiently with minimal costs. This perspective includes lenses, such as transaction cost theory [16], agency theory [23], and incomplete contracts theory [39]. The relational perspective focuses on how organizations develop relationships with external partners and the implications of these relationships for outsourcing [20]. The relational perspective includes lenses such as social exchange theory [10], social capital theory [59], and institutional theory [66].

Crowdsourcing is considered both a strategic and an economic choice for organizations [87]. Firms must weigh strategic and economic benefits against costs before deciding to engage in crowdsourcing activities. Thus, we consider the strategic and economic perspectives relevant to this study. Further, in the context of crowdsourcing, the relationship between solvers and seekers is transaction-based and short term [87,79]. Seekers may not be able to form a relationship with particular solvers because there are usually a large number of solvers for each task and the same solvers may not participate across tasks.[3] Therefore, compared to the strategic and economic perspectives, the relational perspective may be less relevant in this context (cf. [79]). Crowdsourcing involves leveraging the crowd to solve organizational problems rather than solving them internally [44] and is therefore similar to a firm's decision to make vs. buy. Among the theories under the economic perspective, transaction cost theory concerns the decisions of organizations to buy particular products/services from external sources or produce them internally [86]. Thus, we consider it appropriate to include costs in our model.

In addition, crowdsourcing serves as a means for firms to access resources that are unavailable within the organization [54] and to obtain novel solutions from the crowd [12,72]. Given these characteristics, we consider the resource-based view a suitable theoretical lens to understand a firm's crowdsourcing decision because it posits that a firm will look to external sources for resources that are lacking internally [7]. As a complementary lens, the resource-based view (RBV) together with transaction cost theory is used here to explain a seeker's intention to crowdsource.

However, several characteristics differentiate crowdsourcing from outsourcing. First, crowdsourcing aims to recruit undefined individuals to work on organizational tasks [44] rather than recruit selected external vendors in outsourcing. All solvers in the crowdsourcing platform are invited to tackle problems through an open call, in contrast to outsourcing, providing an opportunity for firms to advertise their brands [57] (e.g., brand visibility). Second, the quality of solutions obtained from crowdsourcing is less susceptible to control or guarantee than outsourcing. Solvers in crowdsourcing platforms may not be specialized in a particular area, and some solutions, even if novel, may be difficult to implement [65]. By contrast, in outsourcing, the firm can carefully monitor the development and implementation of the solution to ensure desired quality. Third, in general, multiple solution providers simultaneously work on the same task in crowdsourcing (e.g., solution diversity) but not outsourcing. As a result, firms have more choices of solutions in crowdsourcing and need to expend resources to select the best solution (e.g., proposal evaluation cost). Overall, these differences indicate that firm crowdsourcing requires investigation in its own right. In this study, we have adapted the theories used in the outsourcing literature to crowdsourcing by theorizing the effects of context specific factors (i.e., solution diversity, brand visibility, and proposal evaluation cost), which will be explained next.

2.1. Transaction and production costs in crowdsourcing

Transaction cost theory (TCT), which was initially developed by Coase [16] and extended by Williamson [86,85], is mainly used to identify the conditions under which firms will decide whether to perform certain tasks internally (e.g., make a product or service) or let them be performed by the market (buy). It argues that these decisions are made by balancing two types of costs, *production costs* and *transaction costs*, to achieve efficiency, which is important for organizations to sustain competitive advantage in the market [85]. Production costs are the costs required to make a product or provide a service, such as the cost of capital, labor, and materials. Transaction costs are the coordination costs for the activity, such as searching and planning, information communication, negotiating and process monitoring, and performance evaluation. TCT proposes that firms should perform tasks internally when transactions costs exceed external production savings and outsource tasks when internal production costs are high and present comparative disadvantage [55].

[3] Firms are rewarded with credibility based on the monetary value of transactions in TaskCN. Although the credibility of firms may affect whether solvers take their tasks, it may be less relevant to a firm's intention to crowdsource.

Transaction costs are proposed to depend on various contingencies, such as *asset specificity* and *uncertainty* [86]. Asset specificity refers to durable investments that are undertaken in support of particular transactions, the opportunity cost of which investment is much lower in best alternative uses or by alternative users [86]. The party who has invested in the asset will incur a loss if the party who has not invested withdraws from the transaction. Transactions that are supported by high asset specificity should be governed by hierarchical structures (make internally), whereas transactions that require only general-purpose investments are most efficiently conducted over markets (buy). Uncertainty refers to the cost associated with unexpected outcomes and information asymmetry [55]. Greater uncertainty of a transaction generally implies a higher transaction cost, indicating that the activity should be conducted internally. This premise has been supported by empirical findings that projects with lower uncertainty are outsourced (e.g., [6,32]).

In the context of crowdsourcing, seeker firms are also concerned about the costs of solving their tasks. When making decisions about crowdsourcing, firms consider the efficiency of the decision, i.e., whether production costs are saved and transaction costs are outweighed by the benefits of crowdsourcing. Specifically, the price paid to solve the task in crowdsourcing is the production cost for the seeker. Overall, firms want to ensure that crowdsourcing results in cost reduction. Therefore, we include *cost reduction* as a salient motivator of intention to crowdsource in our model. In addition, transaction costs are incurred during crowdsourcing due to asset specificity and uncertainty. In crowdsourcing, asset specificity is manifested in the form of codification costs. Specifically, firms must expend time and effort to transfer contextual knowledge related to the tasks through careful task requirement codification. We term this *codification cost*, which is tied to the transaction. Codification cost is incurred in support of the transaction and is an opportunity cost if firms fail to obtain satisfactory solutions from crowdsourcing. Furthermore, because uncertainty exists regarding the quality of solutions obtained from crowdsourcing [67], firms may need to expend time and effort to evaluate the proposals from solvers and select winners [2]. We refer to this cost as the *proposal evaluation cost*. Therefore, deriving from TCT and the related literature, we identify and include *cost reduction*, *codification cost*, and *proposal evaluation cost* as antecedents of intention to crowdsource in our model.

While TCT is theoretically and empirically useful, it has been criticized by strategic management researchers [26]. One salient criticism of TCT is that it neglects differential capabilities of firms, i.e., firm heterogeneity [53]. Under the assumption of bounded rationality (as also acknowledged in TCT), the RBV argues that the differential capabilities and resources of firms result in different production costs and that such cost differences influence a firm's decision to make or buy [7]. Thus, firms may internalize activities because they can conduct these activities in a more production (not transaction) cost-efficient way than other firms [26] and buy if needed resources are unavailable within the firm. Therefore, the RBV can complement TCT in explaining a firm's decision to make or buy, and we use these theories in concert in our model to explain a seeker's intention to crowdsource.

2.2. Resources in crowdsourcing

The resource-based view (RBV) argues that valuable resources determine firm performance and competitive advantage in the market [7,61]. According to this theory [7], resources include assets, firm attributes, and information that can contribute to the enhancement of the efficiency and effectiveness of firms' strategies. Valuable resources are neither perfectly imitable nor substitutable without great effort. Thus, sustained competitive advantage can be achieved when firms are able to protect against resource imitation, transfer, or substitution.

The value creation capability of different resources affects the boundary decisions of a firm [61,77]. Firms will attempt to retain activities in-house that take advantage of their strategic resources. Outsourcing these activities would deprive organizations of their competitive advantage and subsequent abnormal returns [22]. However, when needed resources are not available for the activities, firms will look to alternative sources [15,17]. This phenomenon forms the basis for applying the RBV to examine outsourcing decisions in previous studies (e.g., [4,31,37,68]).

In the context of our study, we expect that firms will crowdsource if it provides access to certain beneficial resources that are unavailable internally. A valuable resource that firms can access through crowdsourcing is *brand visibility*, i.e., a reputational resource (cf. [58]). It has been noted that firms may be able to use the crowdsourcing website as a platform to promote the awareness of their brand [87]. In addition, open sourcing can potentially increase customer familiarity with the firm's brand and lead them to accept the brand [3]. Additional knowledge-based resources that seekers can access through crowdsourcing are explained using the resource-based view.

According to the RBV, we expect that firms will consider crowdsourcing if it can fill the gap between the knowledge resources required for solving tasks and the resources available in the firm. The knowledge resources can occur in the form of specialized skills for task solution [12,72] as well as heterogeneity in solutions from a crowd [52,65]. Because crowdsourcing can provide firms access to specialists in various fields, we term this benefit *access to specialized skills*. We term the perceived benefit that crowdsourcing may provide firms with heterogeneous ideas as *solution diversity*. In sum, we include the constructs of *access to specialized skills*, *solution diversity*, and *brand visibility* in our model as drivers of a seeker's intention to crowdsource.

3. Research model and hypotheses

As discussed above, we consider both production- and transaction cost-related factors, i.e., cost reduction, codification cost, and proposal evaluation cost, as well as resources accessible through crowdsourcing, i.e., brand visibility, access to specialized skills, and solution diversity, as antecedents of a seeker's intention to crowdsource in our model (see Fig. 1). Beyond direct effects, we also hypothesize that codification costs and proposal evaluation costs will indirectly impact the dependent variable by diminishing the perceived cost reduction associated with crowdsourcing.

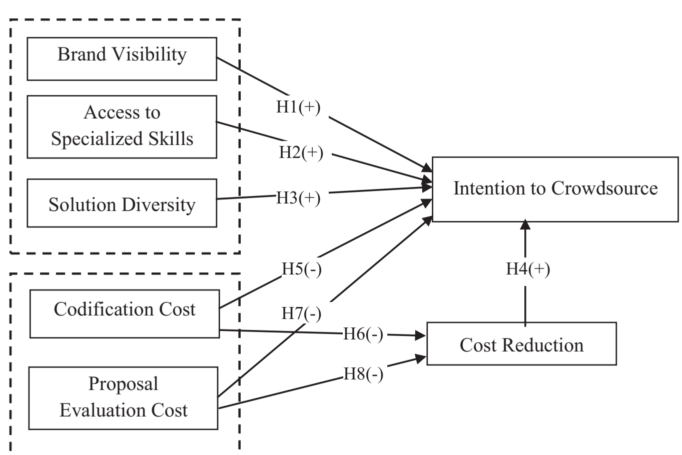

Fig. 1. Research model for a seeker's intention to crowdsource.

3.1. Brand visibility

In this study, brand visibility refers to the extent to which seekers believe that their brands or products will be seen and made aware to a large audience through crowdsourcing. The marketing literature suggests that for an unknown brand, building the brand's knowledge in consumers' minds is a crucial task for a firm [13,76]. Because consumers have limited cognitive capacity and memory for brands [30], they tend to purchase products from familiar brands [76]. The exposure of product information to potential consumers should improve brand familiarity and thus increase purchases [13]. For example, when users are involved in designing a particular product, they are more familiar with and likely to buy it [27,82].

In the context of our study, seeker firms can expect that solvers who perform tasks for the firms in crowdsourcing platforms will be more likely to become aware of and possibly purchase their products/services [93]. Firms believe that the more people are involved in solving tasks for a firm, the more likely they will be able to form an impression about the firm and have a better awareness of their brand [57]. As suggested in the marketing literature, brand image and brand visibility are reputational resources for organizational long-term success [58,1,45]. Because firms believe that crowdsourcing will allow them to reach a large pool of potential solvers and increase brand visibility, according to the RBV, firms may adopt crowdsourcing to acquire the resource (brand visibility) to perform. Following the discussion above, the expected brand visibility could increase a seeker's intention to crowdsource. Thus, we hypothesize the following:

H1. Brand visibility positively affects a seeker's intention to crowdsource.

3.2. Access to specialized skills

We define access to specialized skills as the extent to which firms expect to acquire knowledge or skills related to specific domains through crowdsourcing. Firms can obtain access to a broader range of knowledge, skills, abilities, and opinions through crowdsourcing [73,75]. By leveraging the specialized knowledge and skills of the crowd, firms should be able to tackle internal tasks more effectively. For example, Wilogo taps approximately 13,000 logo design talents to work on tasks proposed by seekers. Through this platform, seekers can approach skilled workers around the world and invite them to design specialized and potentially valuable logos that cannot be obtained from internal employees. Based on a case study in the SAP community, Leimeister et al. [54] suggested that firms could obtain better access to experts through crowdsourcing.

In general, crowdsourcing can allow seeker firms to access the crowd's specialized abilities, which may be unavailable internally, to effectively solve their tasks. As per the RBV, the gap between the knowledge required for task solving and the knowledge available leads firms to believe that they can acquire knowledge externally [61], e.g., through crowdsourcing. Therefore, we expect the following:

H2. Access to specialized skills positively affects a seeker's intention to crowdsource.

3.3. Solution diversity

In this study, solution diversity refers to a seeker firm's perception of the range of different solutions proposed by solvers in crowdsourcing. The basic premise of crowdsourcing is to tap the wisdom of crowds [44]. The heterogeneous skills and knowledge of solvers will contribute to the diversity and innovativeness of solutions obtained from crowdsourcing [9]. The crowd may provide more diverse and novel ideas for problem solving than the relatively homogeneous professional employees in seeker firms [75]. For example, in an experiment involving the design of new products for babies [65], external solvers generated ideas of significantly higher novelty than employees in the firm.

This potential solution diversity provides firms with more choices for solving their problems [44,93], greater potential for innovation [14], and more resources for organizational performance [18]. We argue that these choices will make seeker firms believe they have control of and are satisfied with crowdsourcing. In addition, diverse perspectives from the crowd can allow firms to better understand their needs, reduce the cost of identifying multiple possibilities, and find the best-fit solution. These are invisible resources for organizational superior performance [45]. Thus, as per the RBV, the potential benefit of solution diversity should motivate firms to crowdsource tasks. We propose the following:

H3. Solution diversity positively affects a seeker's intention to crowdsource.

3.4. Cost reduction

We define cost reduction as the perceived cost savings to seeker firms of solving tasks externally through crowdsourcing rather than internally. Cost reduction is a key strategy by which firms improve profitability and maintain competitiveness in the market [16] and has been found to positively impact a firm's decision to outsource [20].

It has been suggested that solving tasks through crowdsourcing can reduce costs [44,12]. Although solvers must be compensated, Brabham's [11] case study of iStockPhoto found that the cost of crowdsourcing was usually lower than that of solving the task internally. Furthermore, an experimental study [43] reported that firms only need to pay a median wage of USD 1.38/h to workers in Amazon Mechanical Turk. If seeker firms perceive a cost advantage of crowdsourcing (lower production cost), as per TCT [86], this advantage should motivate them to crowdsource. Thus, we expect that the perception of cost reduction through crowdsourcing will enhance a firm's intention to adopt this approach. Therefore, we hypothesize the following:

H4. Cost reduction positively affects a seeker's intention to crowdsource.

3.5. Codification cost

Various costs arise for seekers from activities in the crowdsourcing process [2]. In addition to the economic cost of rewarding solvers, we propose that transferring specific knowledge to solvers through clear codification of task requirements is a cost incurred by firms [2]. We define codification cost as the cost to the seeker to codify and describe tasks clearly in crowdsourcing. The codification cost includes the time and effort required to transform the tacit knowledge of the task requirements into explicit information to enable solvers to understand the types of solutions expected.

Clearly defined tasks may produce better solutions from the crowd by reducing the likelihood of irrelevant submissions [75]. In addition, clear task requirements reduce the potential for conflicts between solvers and seekers about solutions that were not selected. However, to clearly define and codify tasks, firms may need to expend both time and effort, i.e., codification costs. The previous literature on knowledge contribution has revealed that individuals will refuse to share knowledge if this action requires a high codification cost [49].

Some tasks require more time and effort for codification if substantial tacit knowledge must be transformed into explicit knowledge. This time and effort could become a sunk cost if firms fail to obtain satisfactory results from crowdsourcing. Thus, as per TCT, a high perceived codification cost indicates a high perceived transaction cost for crowdsourcing [2], which should inhibit firms from adopting the crowdsourcing strategy. Hence,

H5. Codification cost negatively affects a seeker's intention to crowdsource.

The codification cost incurred in crowdsourcing may make firms perceive that crowdsourcing for task solving is not cost-effective. In this sense, codification costs will decrease a firm's perception of cost reduction in crowdsourcing [2]. As per TCT, asset specificity will increase the perception of transaction costs, which will decrease the intention of the target behavior [85,55]. Thus, codification costs should decrease the overall perception of cost reduction as well as behavioral intention. Therefore, we expect the following:

H6. Codification cost negatively affects cost reduction.

3.6. Proposal evaluation cost

We define proposal evaluation cost as the cost associated with assessing submissions and selecting the winners from all solutions obtained from crowdsourcing. An advantage of crowdsourcing is its ability to attract a large number of problem solvers and ideas through an open call [44]. However, this large number of problem solvers and ideas incurs the cost of screening and evaluating these submissions [2]. When a number of proposals are obtained from solvers, seekers believe that they will need to expend considerable time and effort in evaluating those proposals [63]. Given the uncertainty in solution quality, proposal evaluation costs could be a transaction risk or an opportunity cost of solving tasks via crowdsourcing. The transaction risk may become salient to firms when they do not receive a satisfactory submission [90]. If it is costly to evaluate these proposals (high transaction risk), firms may prefer to solve tasks internally to reduce the transaction cost. As per TCT [86], a high perceived proposal evaluation cost will decrease the attractiveness of crowdsourcing for seeker firms. Thus, we expect the following:

H7. Proposal evaluation cost negatively affects a seeker's intention to crowdsource.

As discussed above, the incurred or expected proposal evaluation cost will add to the overall costs of crowdsourcing. Thus, the proposal evaluation cost should decrease the perception of cost reduction of task solving through crowdsourcing. Further, if the solution is highly specific to the firm's application, only the firm can evaluate it. This will further decrease a firm's perception of cost reduction [2]. Therefore, we expect the following

H8. Proposal evaluation cost negatively affects cost reduction.

As explained later in Section 4.3, we also include various control variables in our model because they may partially explain the dependent variable.

4. Research methodology

Survey methodology was employed to test the research model. The survey was conducted in TaskCN.com, one of the most popular and established crowdsourcing websites in China. By the end of September 2014, TaskCN had more than 3.4 million registered solvers and 56 thousand tasks.[4] In contrast to other crowdsourcing platforms, e.g., InnoCentive, solvers in TaskCN interact with crowdsourcing companies to receive additional information via the public online community, private email, or instant messaging [93]. In this context, the company often delivers feedback, including brand-related information, to solvers.

This platform has been recognized as successful for facilitating solutions of a variety of tasks and has received extensive attention from the media in China as well as researchers [88,89,87]. The selection of this platform provides a sufficiently large pool of solvers to test our models. In addition, the availability of previous studies on this platform enables a cumulation of research in this area.

4.1. Instrument development

Because all the construct items in our model were adapted from their original source to the study context, we conducted a systematic procedure of instrument development [19]. First, items for each construct were generated based on the previous literature and refined through interviews with seekers. Second, all items for each construct were validated through unlabeled and labeled sorting exercises. In the two rounds of item sorting, the survey instrument had a high Kappa score, agreement level, and hit ratio, i.e., greater than 0.8, suggesting sufficient construct validity [46]. Finally, prior to the main survey, the instrument was pilot tested with another similar Chinese crowdsourcing website, Zhubajie.com. The final instrument is shown in Table 1. All constructs were reflective, and the items were scored on a 7-point Likert scale anchored from Strongly Disagree to Strongly Agree.

4.2. Control variables

To rule out confounding effects of differences in seeker firm and task characteristics, we also include them as controls in the model that may affect the intention to crowdsource. These variables include a seeker's *firm age*, *firm size*, *previous experience*, *task type* crowdsourced, and *industry*. For instance, smaller and younger firms may be more likely to crowdsource because they lack resources to solve tasks internally and are more concerned with costs [21,34]. A firm's age is measured by the years elapsed since its foundation, while firm size refers to the number of employees. *Industry* is classified by the type of products or services the firm provides. The type of industry was coded as dummy variables in the model. *Previous experience* refers to whether the firm has crowdsourced task(s) to the platform previously. Previous experience is coded as a dummy variable with a value of 0 if the firm has not crowdsourced a task before and 1 otherwise. *Task type* was coded as dummy variables in the model. The demographic information about the respondent firms is listed in Table 2. Among 112 firms crowdsourced in TaskCN, each crowdsourced an average of 1.21 tasks in TaskCN (Min = 1 task, Max = 4 tasks, STD. = 0.72). Only one firm has proposed two types of tasks, i.e., logo design and laborious tasks.

4.3. Data collection

To survey the seeker firms in TaskCN, we obtained a list of registered firms with the assistance of a TaskCN website administrator and randomly selected 500 seekers from the list. We invited these seekers to participate in the survey via email. As a token of appreciation for their participation, a $10 voucher was given to respondents. A total of 161 valid responses were received,

[4] www.taskcn.com.

Table 1
List of survey items.

Constructs	Definition	Source
Cost reduction (COS)	COS1: It is cost effective to solve tasks through crowdsourcing. COS2: Crowdsourcing helps save money in obtaining solutions to our problems. COS3: We can obtain solutions to our tasks at a lower price through crowdsourcing. COS4: It is relatively cheaper to outsource tasks to crowds than other options (i.e., employees or external consultants).	Adapted from Dibbern et al. [20]
Brand visibility (BRD)	BRD1: Crowdsourcing will improve our brand image among the community. BRD2: Crowdsourcing lets more people know (be familiar with) about my firm's brand. BRD3: Crowdsourcing is a way to for our brand products to become known by solvers in the community. BRD4: Crowdsourcing is a good way to promote our brand and products among the community.	Adapted from Sprott et al. [76]
Access to specialized skills (ACC)	ACC1: The platform brings solvers from specific expertise areas to work on tasks. ACC2: There are a number of solvers with specific expertise that we need in the platform. ACC3: The platform can invite a number of solvers with specialized knowledge to work on tasks.	Adapted from Agerfalk and Fitzgerald [3]
Solution diversity (DIV)	DIV1: Different solutions can be obtained through crowdsourcing. DIV2: Solutions obtained by crowdsourcing differ from each other. DIV3: Solutions obtained by crowdsourcing vary greatly. DIV4: Solutions obtained by crowdsourcing represent different ways of thinking about particular tasks.	Adapted from Chen et al. [14]
Codification cost (COD)	COD1: It is difficult to codify our tasks. COD2: It is time-consuming to codify our tasks. COD3: It requires substantial time and effort to write task requirements. COD4: It is difficult to formulate task requirements.	Adapted from Kankanhalli et al. [49]
Proposal evaluation cost (EVA)	EVA1: It is difficult to evaluate how well the tasks are solved. EVA2: It requires time and effort to assess the performance of task solving. EVA3: It is difficult to assess how well tasks have been accomplished. EVA4: It is difficult to select the winners from all submissions.	Adapted from Orpen [60]
Intention to crowdsource (INT)	INT1: We will use this platform for crowdsourcing in the future. INT2: We will crowdsource tasks using this platform in the future. INT3: We intend to use this platform to crowdsource tasks in the future.	Adapted from Zheng et al. [92]

Table 2
Respondent information.

Variables	Frequency ($N = 161$)	Percentage
Firm age (years)		
<1	1	0.62
1–5	100	62.11
6–10	33	20.50
>10	27	16.77
Firm size (number of employees)		
<50	87	54.04
50–100	38	23.60
101–500	22	13.66
>500	14	8.70
Industry		
Advertising and public relations	12	7.45
Education	17	10.56
Financial service and insurance	16	9.94
IT service	42	26.09
Manufacturing	33	20.50
Retailing	16	9.94
Traditional services (e.g., haircut, restaurant)	25	15.52
Previous experience		
0	49	30.44
1		
1 task	95	59.01
2 tasks	12	7.45
3 tasks	4	2.48
4 tasks	1	0.62
Task type		
Website design and programming	21	13.04
Logo design	53	32.92
Writing and translation	43	26.71
Laborious tasks (e.g., post ads in communities)	30	18.01
Others	15	9.32

representing a 32.2% response rate. The respondents included project managers (20.5%), IT managers (17.4%), individual entrepreneurs (37.3%), systems analyst (9.3%), system developers (7.5%), and sales supervisors (8.1%) in charge of the crowdsourcing activities for their respective firms. We verified with the website administrator that this distribution of respondents was representative of the seeker population on the platform.

Because a web-based survey design may suffer from non-response bias [69], we tested for such bias by comparing the early and late respondents [5]. *T*-tests of demographic differences between the earliest 10% respondents and the last 10% respondents revealed no systematic difference. Thus, non-response bias is not expected in this study. We also conducted a Chow's test to check sample homogeneity (Chow 1960). Our results supported sample homogeneity, $F(6, 142) = 1.65$, $p > 0.05$, indicated that different groups of respondents did not answer the questions differently.

5. Data analysis and results

For this study, structural equation modeling (SEM) was chosen to simultaneously analyze all paths among latent variables in one analysis [29]. Within SEM, Partial Least Squares (PLS) was chosen over co-variance-based SEM because single-item constructs (e.g., control variables) are included in the model, which could result in a low model fit in co-variance based SEM. SmartPLS 2.0 software was used to conduct the statistical analyses. All constructs in the model were measured using reflective indicators.

5.1. Instrument validity

To validate our instrument, convergent and discriminant validity tests were conducted [35]. We assessed convergent

Table 3
Exploratory factor analysis.

	1	2	3	4	6	7	8
EVA1	**0.84**	−0.09	0.07	0.08	0.00	−0.29	−0.08
EVA2	**0.80**	−0.16	0.06	0.10	0.11	−0.29	−0.05
EVA3	**0.75**	0.06	−0.12	0.02	−0.02	0.08	0.07
EVA4	**0.86**	0.14	−0.05	−0.02	−0.07	−0.13	−0.07
COD1	−0.04	**0.81**	0.14	0.07	0.12	−0.05	0.10
COD2	−0.03	**0.82**	0.12	−0.02	0.14	−0.03	0.10
COD3	0.01	**0.83**	0.13	0.07	0.14	−0.07	0.14
COD4	0.18	**0.90**	−0.02	0.03	−0.01	−0.08	−0.01
COS1	−0.07	0.12	**0.86**	0.13	0.12	0.18	0.02
COS2	−0.04	0.17	**0.83**	0.25	0.22	0.02	0.02
COS3	−0.06	0.02	**0.87**	0.08	0.20	0.08	0.12
COS4	−0.03	0.09	**0.87**	0.02	0.20	0.13	0.18
BRD1	0.03	0.09	0.13	**0.85**	0.07	0.12	0.12
BRD2	0.01	0.09	0.11	**0.88**	0.20	0.22	0.06
BRD3	0.12	0.00	0.10	**0.89**	0.11	0.20	0.11
BRD4	0.04	−0.01	0.17	**0.81**	0.07	0.28	0.33
DIV1	−0.01	0.12	0.12	0.15	**0.85**	0.24	0.22
DIV2	0.01	0.11	0.26	0.12	**0.85**	0.13	0.13
DIV3	0.12	−0.01	0.26	0.04	**0.88**	−0.05	0.23
DIV4	−0.12	0.21	0.18	0.16	**0.75**	0.06	−0.03
INT1	−0.09	−0.15	0.24	0.24	0.12	**0.91**	0.11
INT2	−0.05	−0.07	0.13	0.32	0.18	**0.94**	0.20
INT3	−0.06	−0.07	0.10	0.28	0.11	**0.93**	0.19
ACC1	−0.01	0.09	0.07	0.09	0.43	0.14	**0.77**
ACC2	−0.08	0.11	0.12	0.17	0.23	0.22	**0.81**
ACC3	0.01	0.18	0.13	0.23	0.01	0.12	**0.87**
Eigenvalue	8.05	4.27	3.34	2.22	1.60	1.22	1.03
% of variance	25.16	13.35	10.44	6.92	5.01	3.81	3.21
Cumulative %	25.16	38.51	48.95	55.87	66.80	70.61	73.82

validity by examining Cronbach's α (CA), composite reliability (CR), average extracted variance (AVE), and factor analysis results [78]. The factor analysis results are shown in Table 3; the factor loading of each item on its own construct was greater than 0.7, as desired. The results in Table 4 demonstrate that each reflective construct in the model has values of CA and CR greater than 0.7 and a value of AVE greater than 0.5. Thus, all constructs satisfied the criteria, demonstrating sufficient convergent validity [35].

Discriminant validity was assessed by examining the indicator-factor loadings and comparing the square root of AVEs with inter-construct correlations [28]. The results in Table 3 show that all indicators loaded more strongly on their corresponding constructs than on other constructs in the model. The results in Table 4 demonstrate that the square root of AVE was larger than the inter-construct correlations. Thus, the constructs demonstrate adequate discriminant validity.

Because the data were collected from a single source, we tested for common method bias. For this purpose, Harman's single-factor test was conducted by performing an exploratory factor analysis with all variables included [64]. The factor analysis produced neither a single factor nor one general factor that accounted for the majority of the variance (21.86% < 50%), as desired. We further included a common method factor in the structural regression model [64] using a PLS approach documented in the literature [56,84]. Additional details and the results are reported in Table A1 in the Appendix. The analysis results show that only 5 of the 30 paths from the common method factor were significant, providing further evidence that the study results were not affected by common method bias.

5.2. Results of hypothesis testing

After validating the measurement model as reported in the previous section, the path (structural) model was tested using SmartPLS 2.0 software. The bootstrapping approach was used, with cases of 161 and samples of 5000 [36].

The hypothesis testing results are shown in Table 5. The path coefficients of the model are shown in Fig. 2 (the coefficients of the

Table 4
Descriptive statistics and correlations.

	Mean	STD	CA	CR	AVE	Age	Size	EXP	DIV	ACC	BRD	COD	COS	EVA	INT
Age	7.04	8.28	–	–	–	–									
Size	302.4	1060.9	–	–	–	0.40	–								
EXP	0.69	0.87	–	–	–	−0.24	−0.15	–							
DIV	5.42	1.19	0.85	0.89	0.69	0.10	0.13	0.08	0.83[a]						
ACC	5.99	0.99	0.75	0.86	0.67	0.12	0.54	0.07	0.54	0.82[a]					
BRD	5.25	1.26	0.88	0.93	0.81	0.12	0.37	0.07	0.39	0.47	0.90[a]				
COD	5.16	1.17	0.88	0.90	0.70	0.09	0.22	−0.01	−0.24	−0.09	−0.24	0.84[a]			
COS	5.85	1.06	0.88	0.91	0.78	0.10	0.51	−0.02	0.51	0.41	0.36	−0.40	0.88[a]		
EVA	4.61	1.44	0.81	0.89	0.73	0.00	−0.01	−0.01	0.01	−0.14	0.03	−0.09	−0.12	0.85[a]	
INT	5.81	1.39	0.92	0.95	0.86	0.15	0.31	0.04	0.33	0.48	0.53	−0.28	0.48	−0.15	0.93[a]

Notes: COS, cost reduction; BRD, brand visibility; ACC, access to specialized skills; DIV, solution diversity; COD, codification cost; EVA, proposal evaluation cost; INT, intention to crowdsource; age, firm age; size, firm size; EXP, previous experience; STD, Std Dev.; CA, Cronbach's α; CR, composite reliability; AVE, average variance extracted.
–, Excluded because it was a single measure.
[a] Diagonal elements are the square root of AVE.
+ Dummy variables, i.e., task type and industry, are not included in the correlation table.

Table 5
Results of hypothesis testing.

	DV = intention to crowdsource		DV = cost reduction	Result
	Control	Main effect	Main model	
Firm age	0.11*	0.08†		Sig.
Firm size	0.04	0.01		N.S.
Industry (baseline traditional service)				
Advertising and public relations	0.004	0.09		N.S.
Education	0.21*	0.14*		Sig.
Financial service and insurance	−0.07	−0.07		N.S.
IT service	0.15	0.08		N.S.
Manufacturing	0.19	0.13		N.S.
Retailing	0.13	0.11		N.S.
Previous experience	0.05	0.04		N.S.
Task type (baseline others)				
Website design and programming	0.01	0.01		N.S.
Logo design	0.02	0.03		N.S.
Writing and translation	0.03	0.01		N.S.
Laborious tasks	−0.08	−0.07		N.S.
Brand visibility (BRD)		**0.35*****		**H1 supported**
Access to specialized skills (ACC)		**0.19****		**H2 supported**
Solution diversity (DIV)		−0.04		H3 not supported
Cost reduction (COS)		**0.21****		**H4 supported**
Codification cost (COD)		**−0.10***		**H5 supported**
			−0.40***	**H6 supported**
Proposal evaluation cost (EVA)		**−0.19*****		**H7 supported**
			−0.11*	**H8 supported**
R^2	0.09	0.47	0.17	
Observations			161	

† $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

control variables are not included and can be found in Table 5). As shown in Table 5, the model explains 47% of the variance in seekers' intention to crowdsource, indicating an acceptable predictive capability of our model in explaining the dependent variable. As expected, cost reduction, brand visibility, and access to specialized skills are positively related to a seeker firm's intention to crowdsource (H1, H2, and H4 are supported), while codification cost and proposal evaluation cost are negatively related to the dependent variable (H5 and H7 are supported). Codification cost and proposal evaluation cost have significant negative impacts on cost reduction, indicating that H6 and H8 are supported. Contrary to our prediction, solution diversity has no impact on a firm's intention to crowdsource (H3 not supported), possibly due to the nature of the crowdsourced tasks in our sample. The crowdsourced tasks may not have required high creativity to solve, and thus the firms did not consider solution diversity an important driver for crowdsourcing. Among the control variables, firm age (marginally) and education industry were positively related to seeker firms' intention to crowdsource. This suggests that older firms tend to have a higher intention to crowdsource and that firms in the education industry are more likely to crowdsource their tasks than those in traditional services industries (the baseline).

We also conducted the Sobel test to examine the mediation effects of cost reduction for codification and proposal evaluation costs following [8] method. Two additional PLS models were evaluated: one containing only direct paths from the independent variables to the mediator and one containing paths from both independent variables and the mediator to the dependent variable. As indicated in Table 6, cost reduction partially mediates the relationship between codification cost and intention to crowdsource as well as between proposal evaluation cost and the dependent variable.

We also tested the mediation effects following [40] bootstrapping method, as shown in Table 7. The bootstrapping β for the mediating effect of the relationship between codification cost and intention to crowdsource was −0.07 (CI = −0.13 to −0.03), while the value for the relationship between proposal evaluation cost and intention to crowdsource was −0.05 (CI = −0.10 to −0.04). The value of 0 was not included in the 95% confidence interval for both mediating β. These results are consistent with those shown in Table 6. Therefore, the mediation effects of cost reduction are further confirmed.

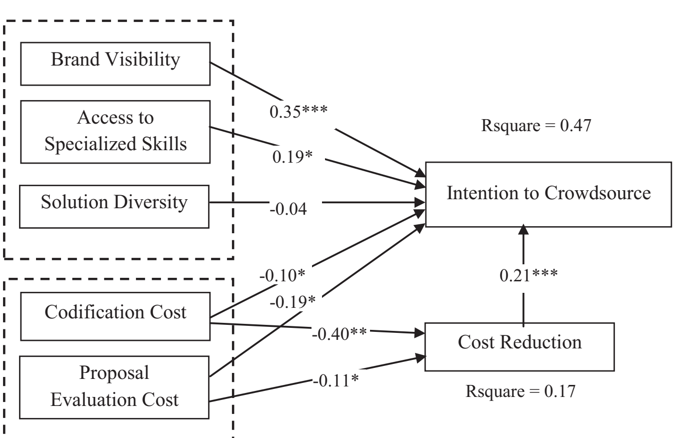

Fig. 2. Path coefficients.

Table 6
Sobel test for mediating effects.

Path	Coefficient	Standard error of coefficient	Sobel test (T-value)
COS → INT	0.43***	0.049	N.A.
COD → COS	−0.42***	0.038	6.87***
EVA → COS	−0.15*	0.066	3.37***

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

Table 7
Bootstrapping test for mediating effects.

Relations	Coefficient	T-value	Bootstrapping β	Confidence interval (95%)	
				Lower	Upper
Independent variable → mediator (a path)					
COD → COS	−0.42	6.20***			
EVA → COS	−0.11	2.12*			
Mediator → dependent variable (b path)					
COS → INT	0.43	5.35***			
Independent variable → dependent variable (c path)					
COD → INT	−0.18	2.78**			
EVA → INT	−0.23	2.67**			
Independent variable → dependent variable (c′ path)					
COD → INT	−0.10	2.13*			
EVA → INT	−0.19	2.02*			
Mediating effects					
COD → COS → INT			−0.07	−0.13	−0.03
EVA → COS → INT			−0.05	−0.10	−0.04

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

5.3. Post hoc analysis

Because the surveyed seeker firms included those who have crowdsourced a task to TaskCN in the past and those who have not, this study post hoc tested for a difference in the antecedents of future intention to crowdsource between the two groups of seeker firms. Of the 161 firms in our sample, 49 seeker firms have registered but have not submitted a task in TaskCN (inexperienced seeker firms), while 112 seeker firms have prior experience in crowdsourcing through TaskCN (experienced seeker firms). We split the sample into these two groups and tested the hypotheses separately for each group. The approach of Keil et al. [51] was adopted to statistically compare the corresponding path coefficients for the two groups and compute the T-values shown in Table 8.

Table 8 shows that significant differences exist between inexperienced and experienced seeker firms in the antecedents of intention to crowdsource. Inexperienced seekers pay more attention to cost reduction, codification cost and proposal evaluation cost, while experienced seeker firms give more importance to brand visibility and access to specialized skills. We did not compare the coefficients for solution diversity because neither was significant.

The differences between the two groups could be due to changes in beliefs as seekers gain experience with crowdsourcing. According to the belief-adjustment model [42], people revise their beliefs over time. Specifically, they will first develop a general perception of an action. Their beliefs will then be revised as new information is received. Positive information will result in a relatively small increase in the strength of current beliefs, while negative information will result in a considerable decrease in the strength of existing beliefs. Similar arguments are found in cognitive dissonance theory [25]; as individuals gain first-hand experience, they evaluate the extent to which their initial cognition (or beliefs) is consonant or dissonant with actual experience and revise their cognition or behavior to achieve greater consonance.

In the context of our study, seekers have a general perception of crowdsourcing before their participation. Their beliefs will be revised based on their actual experience and information gained from crowdsourcing. Seekers will evaluate whether their initial cognition is consonant with actual experience and revise their cognition and behaviors accordingly. Thus, it is possible that the feedback from the crowdsourcing experience significantly changed seekers' beliefs such that cost-related factors became less salient (cost reduction, codification cost and proposal evaluation cost) and resource factors became more salient (brand visibility and access to specialized skills). Our interviews with a few experienced seekers confirm an overall positive experience, in that the resources from crowdsourcing were apparent to them and the costs were not too burdensome. However, the extent of cost reduction they expected may not have materialized. We refrain from generalizing these results because the samples may not be sufficiently large; the differences between the groups need to be investigated in greater depth in the future.

6. Discussion and implications

With the emergence of new Internet-based technologies, firms are starting to leverage the wisdom of the crowd to solve internal tasks. To increase firm participation, crowdsourcing platforms should understand what motivates firms to crowdsource [91]. This understanding is essential because not every crowdsourcing platform has been successful in attracting and retaining firms to crowdsource their tasks, as exemplified by the failure of CrowdSpirit.[5] Furthermore, studies of theoretical modeling and empirical testing of the antecedents (including costs) of firms' intention to crowdsource (see a thorough review by Zhao and Zhu [91]) have been limited. Therefore, researchers and practitioners alike are interested in understanding how to encourage firms to crowdsource tasks [44,80]. From the perspective of seeker firms, participation in crowdsourcing may allow them to obtain benefits. Deriving from the RBV and TCT and following the call of Zhao and Zhu [91] for additional research, this study developed a model to explain firms' intention to crowdsource. Cost reduction, brand visibility, and access to specialized skills were found to positively affect the intention to crowdsource, while codification cost and proposal evaluation cost negatively affect this intention. In addition, cost reduction was found to partially mediate the influences of codification cost and proposal evaluation cost on the intention to crowdsource.

6.1. Limitations and future research

The findings of this study should be interpreted in light of its limitations. First, our study is restricted in its ability to make broad generalizations because only one type of crowdsourcing platform was studied. In other websites such as InnoCentive, seeker firms crowdsource tasks that require greater creativity and expertise to solve, e.g., R&D problems. Future research could examine seeker firms in crowdsourcing platforms such as InnoCentive [48] to determine if similar results hold or factors such as solution diversity become salient. Nevertheless, this study has established some degree of generalization because similar results have been obtained in both a pilot test in another Chinese crowdsourcing platform (zhubajie.com) and the main study in TaskCN. Thus, the findings may be generalizable to platforms that are similar in the types of tasks to be solved, incentives provided, and crowdsourcing mechanism used, e.g., Wilogo.com, TopCoder.com, and Netflix.com.

Second, while this paper studied the influence of cost and resource factors on firms' intention to crowdsource within a platform, future work could explore the influence of the characteristics of different crowdsourcing platforms on seeker firms' crowdsourcing behavior. In particular, researchers could

[5] http://www.crowdsourcing.org/document/lessons-from-the-failure-of-crowd-sourcing-platform-crowdspirit/4086 (accessed 18.05.13).

Table 8
Post hoc comparison.

	COS → INT	BRD → INT	ACC → INT	COD → INT	EVA → INT
Path coefficient (standard error)					
Inexperienced	0.25 (0.060)	0.28 (0.065)	0.24 (0.066)	−0.26 (0.078)	−0.20 (0.040)
Experienced	0.08 (0.052)	0.42 (0.056)	0.30 (0.063)	−0.23 (0.053)	−0.18 (0.034)
S_{pooled}	0.057	0.061	0.064	0.062	0.326
T-test across groups	18.02***	−13.72***	−5.60***	−2.84**	−3.25**

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

investigate the performance of crowdsourcing platforms in facilitating the process of crowdsourcing. For example, crowdsourcing platforms could be considered knowledge brokers in the framework of knowledge brokering theory [38] to explore the performance of crowdsourcing platforms. Furthermore, researchers should conduct longitudinal research on the antecedents of organizations' actual crowdsourcing behaviors by collecting the number of tasks crowdsourced by companies in future.

Third, we found a partial mediating effect of cost reduction on the influence of codification cost and proposal evaluation cost on the intention to crowdsource. Future research should theoretically explore the underlying (both cost- and non-cost-related) mechanisms that link proposal evaluation cost and codification cost to intention to crowdsource. Furthermore, future studies should explore the relationship between solution diversity and proposal evaluation cost because diverse solutions may increase the workload for firms to select a winning solution.

6.2. Theoretical contributions

This paper contributes to the crowdsourcing literature by developing a holistic model to explain firms' intention to crowdsource and empirically testing it with survey data. This study contributes to research in several ways. First, the understanding of seeker firms' crowdsourcing behavior in the previous literature has been mainly based on conceptual or case studies (e.g., [12,72,87,81]). Following the call by Zhao and Zhu [91] for additional research, this paper fills the literature gap by theoretically and empirically exploring the antecedents of firms' intention to crowdsource. This study found that cost reduction, brand visibility, and access to specialized skills positively affect firms' intention to crowdsource. This study adds to the crowdsourcing literature by validating these considerations as important for firms' crowdsourcing decisions.

Second, previous studies mainly suggested an influence of benefit factors on firms' crowdsourcing behavior [21,52]. There has been a lack of investigation of the influences of costs on crowdsourcing [2]. This paper identified the cost constructs for this context and tested them in the TaskCN platform, finding that codification cost and proposal evaluation cost negatively affect firms' intention to crowdsource. These findings contribute to the crowdsourcing literature by enriching our understanding of the cost concerns that thwart firms' intention to crowdsource.

Third, this study found that certain antecedents of crowdsourcing intention, i.e., cost reduction and access to specialized skills, are similar to the determinants of outsourcing decisions (cf. [47]). However, several antecedents differ and are specific to firms' intention to crowdsource, i.e., brand visibility, codification cost, and proposal evaluation cost. These context-specific findings contribute to previous research by enabling a comparison of the two forms of sourcing. Furthermore, this study facilitates future research by developing and validating an instrument for studying firms' crowdsourcing behavior.

Fourth, this study contributes to the literature on TCT and the RBV. It extends the applicability of transaction cost theory and the resource-based view to the context of crowdsourcing. The explanatory power and support for the model indicate that the complementary perspectives of TCT and the RBV provide an appropriate theoretical lens to explain firms' intention to crowdsource, i.e., our results suggest that both cost and resource factors affect firms' intention to crowdsource. Furthermore, we modified the standard TCT and RBV formulations to account for firms' intention to crowdsource by modeling the influence of context-specific constructs, i.e., brand visibility, codification cost, and proposal evaluation cost.

6.3. Practical implications

From a pragmatic perspective, this study provides crowdsourcing platform administrators insights on how to attract firms to crowdsource their tasks in two main ways. First, this study provides guidelines for crowdsourcing platforms to enhance firms' intention to crowdsource. In particular, the results of this study suggest that crowdsourcing platforms should heighten the perceptions of the benefits of cost reduction, brand visibility, and access to specialized skills to promote firms' participation in crowdsourcing. Crowdsourcing platforms should take the initiative to attract and retain a large and diverse pool of solvers to participate in crowdsourcing so that firms can access their specialized skills in multiple areas. In addition, crowdsourcing platforms should communicate to firms the cost-effective advantage of solving tasks through crowdsourcing. Inviting experienced seeker firms to share their crowdsourcing experience could be a viable approach for crowdsourcing platforms to advertise the benefits of crowdsourcing. A forum could also be established to obtain feedback and comments from firms on their crowdsourcing experience.

Second, crowdsourcing platforms should seek ways to reduce the costs of firm participation while maintaining profitability. Crowdsourcing platforms should identify approaches to facilitate the codification of requirements and provide firms with appropriate tools to support task codification. In particular, crowdsourcing platforms could help firms define their problems by providing specific advice and improve the process of requirement submission by offering tools to support firms, e.g., providing samples and training for requirement codification. In addition to reducing codification effort, crowdsourcing platforms should strive to mitigate firms' proposal evaluation costs by providing appropriate tools for firms to filter out irrelevant proposals, e.g., by refined searching. Crowdsourcing platforms can also offer services to assist firms with the selection of relevant solutions according to the task requirements.

7. Conclusion

Considering the importance of seeker firm participation to the survival of crowdsourcing platforms, practitioners have expressed substantial interest and concerns about encouraging

Table A1
Common method bias analysis.

	Items	Factor path/loading (original sample)	Factor squared loading (R^2)	*T*-value	Method path/loading (original sample)	Method squared loading (R^2)	*T*-value
Brand visibility	BRD1	0.84	0.71	**20.13**	0.03	0.00	0.52
	BRD2	0.94	0.88	**18.39**	−0.08	0.01	1.63
	BRD3	0.98	0.96	**32.33**	−0.12	0.01	**2.94**
	BRD4	0.64	0.41	**10.37**	0.21	0.04	**3.01**
Cost reduction	COS1	0.84	0.71	**18.13**	0.00	0.00	0.06
	COS2	0.86	0.74	**19.55**	0.01	0.00	0.17
	COS3	0.92	0.85	**31.82**	−0.01	0.00	1.65
	COS4	0.82	0.67	**16.65**	0.07	0.00	1.43
Access to specialized skills	ACC1	0.54	0.29	**4.13**	0.14	0.02	1.16
	ACC2	0.97	0.94	**17.91**	−0.16	0.03	**2.61**
	ACC3	0.91	0.83	**21.82**	−0.04	0.00	0.64
Solution diversity	DIV1	0.81	0.66	**13.58**	0.02	0.00	0.36
	DIV2	0.79	0.62	**13.51**	0.06	0.00	0.92
	DIV3	0.92	0.85	**18.29**	−0.05	0.00	0.79
	DIV4	0.81	0.66	**13.61**	−0.03	0.00	0.48
Proposal evaluation cost	EVA1	0.80	0.64	**21.25**	−0.05	0.00	0.99
	EVA2	0.86	0.74	**32.81**	0.03	0.00	0.71
	EVA3	0.84	0.71	**27.39**	0.01	0.00	0.06
	EVA4	0.82	0.67	**25.52**	0.01	0.00	0.26
Codification cost	COD1	0.91	0.83	**47.48**	−0.07	0.00	0.45
	COD2	0.92	0.85	**41.06**	0.06	0.00	0.53
	COD3	0.88	0.77	**31.79**	−0.02	0.00	1.54
	COD4	0.76	0.58	**14.17**	0.01	0.00	1.25
Intention to crowdsource	INT1	0.93	0.86	**28.02**	−0.03	0.00	0.88
	INT2	0.91	0.83	**39.31**	0.05	0.00	1.66
	INT3	0.94	0.88	**31.41**	−0.02	0.00	0.51

firms to crowdsource [21]. Moreover, research on and understanding of the factors that influence a firm's intention to crowdsource have been lacking. To this end, we developed a model based on transaction cost theory and the resource-based view to examine drivers and inhibitors of firms' intention to crowdsource. Our findings indicate that cost reduction, access to specialized skills, and brand visibility enhance a firm's intention to crowdsource, while proposal evaluation costs and codification costs reduce a firm's intention to crowdsource, both directly and indirectly. These findings add to the limited but growing body of research on crowdsourcing. They also offer suggestions for practitioners to provide appropriate motivators and help reduce participation cost to promote crowdsourcing by firms.

Appendix A. Common method bias analysis

Following the PLS approach of Liang et al. [56] and Wells et al. [84], an unmeasured latent method construct (ULMC) was included in the structural regression model to assess common method bias (CMB). The analysis results are shown in Table A1. The results suggest that all original factor loadings (from the measurement items to the related latent construct) remained significant, as did the hypothesized paths in the structural regression model. Only 5 of the 30 paths from the ULMC to the measurement items were significant. The loading magnitude of 5 significant paths was substantially smaller than the corresponding loading to the related latent construct. This provides further evidence that the study results were not affected by CMB.

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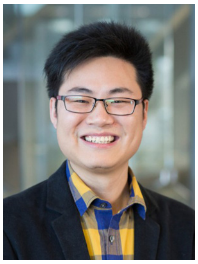

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