HOW SOCIAL SUBSYSTEM AND TECHNICAL SUBSYSTEM RISKS INFLUENCE CROWDSOURCING PERFORMANCE

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Abstract

Crowdsourcing is an effective and powerful tool for firms to solve practical issues and develop innovative products, but the relationship between risks and performance in crowdsourcing has received insufficient attention. Based on a dataset of 163 samples from China, social subsystem risk is empirically found to negatively influence crowdsourcing performance, whereas technical subsystem risk affects the performance insignificantly. The negative impact of social subsystem risk on performance is stronger than that of technical subsystem risk. These findings reveal that different types of risk have diverse roles in affecting performance. Moreover, we provide novel knowledge to existing literature by empirically indicating that different risk types interact with one another to influence performance. Technical subsystem risk particularly enhances the negative effect of social subsystem risk on performance. Therefore, crowdsourcers should develop systematic but different risk management strategies to mitigate the two risk types.

Keywords: Crowdsourcing performance, Socio-technical theory, Risk management, Crowd participant.

1 INTRODUCTION

Crowdsourcing is an effective and powerful tool for firms to solve practical issues and develop innovative products. Numerous firms increasingly outsource tasks to unknown individuals through the Internet (Borst 2010; Zheng et al. 2011). In crowdsourcing, tasks that are traditionally executed by internal employees are accomplished by groups or individuals outside the organization (Howe 2006). Crowd participants can contribute significantly to the future success of businesses because business tasks can be completed at low cost and in a short time (Howe 2008).

Although crowdsourcing can generate many benefits (e.g., cost reduction and innovation promotion), crowdsourcing performance is pessimistic. For example, Kittur (2010) found that almost 50% of crowd workers delivered useless or reduplicate outcomes when he posted a particular task in an online crowdsourcing platform (i.e., Mechanical Turk). Robertson et al. (2009) also found that the quality of results received from crowd workers in crowdsourcing platforms was poor. These facts indicate that previous crowdsourcing tasks performed unsatisfactorily and exercised poor risk management.

Surprisingly, despite prior literature identifying numerous factors (e.g., intrinsic motivation and compensation mechanism) that may positively affect crowdsourcing performance (Morris et al. 2012; Morris et al. 2013; Mason & Watts 2009), attempts to investigate this issue from the perspective of risk are insufficient. Previous research indicates that risks are embedded within the crowdsourcing context and may generate unfavorable outcomes. For example, Rogstadius et al. (2011) suggested that crowdsourcing task involved various issues that may result in poor performance. Borst (2010) argued that crowdsourcers suffered high risks that contributed to low task quality. However, empirical evidence on the relationship between risk and crowdsourcing performance is lacking. Empirical findings on the risk–performance relationship in the traditional outsourcing context are also contradictory. Some researchers determined that risk has a negative effect on performance, whereas other researchers found that the same type of risk insignificantly affects performance (Taylor 2007; Aundhe & Mathew 2009; Liu & Wang 2014). The different challenges that crowd participants face compared with traditional workers may changes the effect of risk on performance (Rogstadius et al. 2011). Therefore, an extensive exploration of the risk–performance relationship in the context of crowdsourcing is necessary.

Extant research that focuses on risk–performance relationship also fails to compare the influences exerted by various risk types. Different risk types may generate various performance levels (Wallace et al. 2004; Liu & Wang 2014). Based on socio-technical theory, risks can be classified into two dimensions: social subsystem (i.e., issues associated with related parties and the uncertainty surrounding the social relationships of the parties) and technical subsystem (i.e., technological uncertainty and complexity surrounding tasks). Empirical evidence in the context of outsourcing shows that while social subsystem risk significantly influences performance, technical subsystem risks insignificantly affect performance (Liu & Wang 2014). This result implies the different effects of social subsystem and technical subsystem risks on performance. However, given that high technological uncertainty and unstable social relationships are involved in crowdsourcing, a direct contrast between the influences of social subsystem and technical subsystem risks is essential. Understanding this issue enables managers to focus on and mitigate the most significant risks in managing crowdsourcing tasks.

Regardless of the simultaneous prevalence of different risk types, the issue on the interaction between social subsystem and technical subsystem risks has received insufficient attention. No attempt has been made to address this issue in both risk management literature and outsourcing and crowdsourcing literature. This situation may generate practical problems because managers may find that improving performance by merely mitigating one type of significant risk is ineffective if social subsystem and technical subsystem risks function as complements.

The issue on whether technical subsystem risk weakens or strengthens the impact of social subsystem risk is equivocal based on two theoretical views in previous studies with opposing arguments. The risk-based view asserts that worse performance is obtained if more risks are present, and factors such as technical uncertainty can enhance the negative effect of social-related risk on project performance (Wallace & Keil 2004). However, a competing adaptation view argues that technical-related risk weakens the negative impact of social-related risk because social interactions increase and more information exchange occur in the presence of technological uncertainty (Hong & Hartley 2011). These contradicting viewpoints require further theoretical development on the interactive effect among different risk types.

The current study addresses the aforementioned research gaps by investigating the following research questions. (1) How do social subsystem and technical subsystem risks affect crowdsourcing performance? (2) What is the relative effect of social subsystem and technical subsystem risks on crowdsourcing performance? (3) How do social subsystem and technical subsystem risks interact to influence crowdsourcing performance?

This paper is structured as follows. First, we introduce relevant theoretical background and develop a conceptual framework. Second, we present our research model and hypotheses. Third, we elaborate our methodology and empirically test each hypothesis by analyzing data collected from China via hierarchical regression analysis. Finally, we present the research results and discuss both theoretical and managerial implications.

2 THEORETICAL DEVELOPMENT

2.1 Crowdsourcing Risk

Risk management is regarded as an effective way to promote task performance (Spears & Barki 2010; Bakker et al. 2010). Previous studies defined risk as a condition that seriously threatened the successful completion of a task (Liu et al. 2010; Liu & Deng 2015). Numerous risks have been identified in previous research (Wallace et al. 2004; Liu et al. 2010). Measures of risk factors in outsourced projects have also been developed and validated. Nakatsu and Iacovou (2009) classified risks in outsourced projects into 11 dimensions based on literature review and the Delphi process. Wallace et al. (2004) developed a list of risk factors and mapped these factors into six dimensions based on socio-technical theory. However, crowdsourcing risks were rarely identified and classified.

Previous researchers argued that crowdsourcing was a complicated socio-technical system (Kittur et al. 2013). Diverse social and technical elements, such as Internet platforms, organization, and human behavior constitute the system. Socio-technical theory emphasizes the fit between two components of the system—technical and social subsystems (Trist 1981) and is applied to identify and categorize risks in project management and outsourcing (Wallace et al. 2004; Liu & Wang 2014). Therefore, this theory is adopted in the present study to develop the dimensions of risk in crowdsourcing.

This study conceptualizes six types of risks based on previous studies, namely, crowdsourcer, relationship, crowdsourcee, complexity, requirement, and task risks. Crowdsourcer, relationship, and crowdsourcee risks belong to social subsystem risk; whereas complexity, requirement, and task risks belong to technical subsystem risk. In traditional socio-technical theory, the social system comprises people, their social relationships, and the values, attitudes, skills, and knowledge that they put into work environments (Bostrom & Heinen 1977). Thus, in the crowdsourcing context, crowdsourcer, crowdsourcee, and relationship are three significant dimensions of social subsystem risk because crowdsourcer and crowdsourcee are the major roles involved in a crowdsourcing task. The technical system comprises the task and technology that are required to transform inputs into outputs (Bostrom & Heinen 1977). Wallace et al. (2004) further develop two dimensions of technology (i.e., complexity and requirement) for both internal and outsourced projects. Therefore, complexity, requirement, and task are adopted as the three major dimensions of technical subsystem risk in the context of crowdsourcing.

Social subsystem risk refers to issues and uncertainties associated with the social environment. In social subsystem risk, crowdsourcer risk refers to the lack of crowdsourcer involvement during task implementation. Crowdsourcer risk is closely related to the attitude and participation of crowdsourcers (Rai et al. 2009). In the crowdsourcing scenario, taking a proactive role to collaborate with crowdsourcees is challenging for a crowdsourcer. Thus, crowdsourcer risk is very likely to occur in crowdsourcing. Relationship risk refers to the poor interaction between crowdsourcer and crowdsourcee, which increases the uncertainty of task completion. Relationship risk often manifests a lack of effective communication, poor relationship, and insufficient trust (Ikediashi et al. 2012). Sponsors and crowd workers from diverse backgrounds in crowdsourcing increase relationship risk (Kannangara & Uguccioni 2013). Crowdsourcee risk refers to the lack of capability and experience of crowdsourcees. The quality of task outputs largely relies on the experience and ability of crowdsourcees. Typical crowdsourcee risks, such as lack of sufficient knowledge and experience, increase the uncertainty of task outcomes (Estellés-Arolas & González-Ladrón-de-Guevara 2012).

Technical subsystem risk reflects issues and uncertainties associated with the technical environment. Complexity, requirement, and task risks are three sub-dimensions of technical subsystem risk. Complexity risk refers to the inherent complexity and difficulty of a crowdsourcing task. Complexity risk also reflects the extent to which complicated technology and complex knowledge are involved in a task. Requirement risk refers to the uncertainty surrounding task requirements. Incorrect requirements, and ambiguous and unclear requirements are typical requirement risk factors. Requirement risk can interfere with the predictable progress of task execution (Keil et al. 2013). Task risk refers to the structural uncertainty of tasks. Too many sub-tasks and high interdependency among sub-tasks lead to high task uncertainty (Li & Wieringa 2001).

2.2 Risk and Performance

The correlation between risk and performance has been documented intensively in the context of outsourcing (Taylor 2007; Liu & Wang 2014). However, the risk–performance relationship in the field of crowdsourcing is insufficiently understood. Rogstadius et al. (2011) have indicated that the situation will become more complicated in crowdsourcing. Crowdsourcees are situated in an uncertain environment. A crowdsourcer may be unfamiliar with the crowdsourcee who works for the tasks. Diverse backgrounds of crowd workers may also increase relationship risk and significantly interfere with task implementation (Kannangara & Uguccioni 2013). Nevertheless, some risks, such as task risk, may insignificantly influence crowdsourcing performance because various sub-tasks can be completed by enormous crowd participants. Thus, several risks that are significant in the context of outsourcing may insignificantly influence performance in crowdsourcing. Further research is required to clarify this issue.

Although the risk–performance relationship has been examined in prior literature, little research has attempted to compare the effects of different risks on performance. Understanding this issue is important because managers can prioritize investing limited resources and time on mitigating significant risks to foster crowdsourcing performance. Despite the absence of comparisons of risk impact, previous studies implied that the effects of various risks differed. Based on a survey of 55 project managers, Kappelman et al. (2006) indicated that people-related risks were more significant than technical-related risks. Liu and Wang (2014) found that social subsystem risk significantly influenced the performance of outsourced projects, but technical subsystem risk insignificantly affected performance. In the crowdsourcing context, the negative impact of social subsystem risk is intensified because high uncertain relationships and unobservable parties are involved in crowdsourcing. Crowdsourcees also have diverse backgrounds without any formal restraints (Wexler 2011). In such situations, the negative influence of social subsystem risk is intensified. Based on the above arguments and findings, the negative effect of social subsystem risk on performance is supposedly stronger than that of technical subsystem risk.

2.3 Interactions between Social Subsystem and Technical Subsystem Risks

Given that social and technical subsystem risks are likely to occur simultaneously in crowdsourcing, investigations on the joint effect of both risks is a critical research issue. However, previous theories provided opposing arguments and evidence on the interactive effects of these risks. According to a risk-based view, Wallace and Keil (2004) have argued that performance is worse if more risks are present; thus, technical-related risk strengthens the negative effect of social-related risk. However, an adaptation view claims that social activities are more intensive and effective when a technical-related risk occurs (Hong & Hartley 2011). Oh and Rhee (2008) also found that the effectiveness of buyer–supplier collaboration increased under the environment of technological uncertainty. Therefore, the interactive effect of social subsystem and technical subsystem risks on performance requires further investigation.

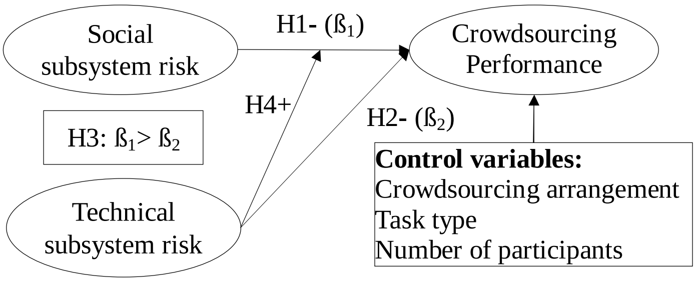
We posit that technical subsystem risk is viewed as complementary to social subsystem risk and strengthens the negative effect of social subsystem risk on crowdsourcing performance. This assertion is made based on socio-technical theory, which contends that a social system is more significant for performance in the presence of a technical system (Bostrom & Heinen, 1977； Wallace et al. 2004; Khan et al. 2014). Given that social subsystem risk belongs to the social system and technical subsystem risk is attributed to the technical system, the negative impact of social subsystem risk increases with high levels of technical subsystem risk. In crowdsourcing platforms, technological uncertainty and complexity increase the instability and uncertainty in an intangible social environment, thereby impairing crowdsourcing performance.

2.4 Crowdsourcing Performance as the Dependent Variable

Crowdsourcing performance is defined as the extent to which the crowdsourcing task is completed in an efficient way and with satisfactory outputs (Mao et al. 2008; Zhu et al. 2014). It captures both the effectiveness of crowdsourcing outcomes and the efficiency of processes. Such performance can also be appropriately evaluated by crowdsourcees.

3 RESEARCH MODEL AND HYPOTHESES

The research model in Figure 1 is presented based on the above mentioned arguments. First, the effects of social subsystem and technical subsystem risks on performance are investigated. Next, the relative effects of these risks are compared. Finally, the interactive effects of these two risks on performance are studied.



- Crowdsourcer risk, relationship risk and crowdsourcee risk are the first-order constructs of social subsystem risk.
- Complexity risk, requirement risk, and task risk are the first-order constructs of technical subsystem risk.
- $ß_1$ is the path coefficient between social subsystem risk and performance.
- $ß_2$ is the path coefficient between technical subsystem risk and performance.

Figure 1. Research model.

Crowdsourcing performance is negatively influenced by risks embedded within the social environment, such as uncertainty between crowdsourcer and crowdsourcee. Satisfactory outcome is unlikely with an untrusting relationship between crowdsourcer and crowdsourcee. Lack of effective communications also makes accomplishing tasks with the crowdsourcer expectations difficult. Moreover, if a crowdsourcer lacks involvement during task implementation, crowd workers cannot obtain enough support and guidance from the crowdsourcer and tasks cannot be completed efficiently. The performance will also worsen if a crowd worker is incompetent for a task. Output quality largely relies on the capability a crowd worker. Lack of sufficient knowledge, experience, and skills from a crowdsourcee often leads to low-quality outcomes (Estellés-Arolas & González-Ladrón-de-Guevara 2012). Therefore, we propose the following hypothesis.

H1: Social subsystem risk negatively affects crowdsourcing performance.

Crowdsourcing tasks with high complexity levels can cause a series of difficulties for crowd workers. High technological complexity costs participants considerable time and energy to accomplish tasks, thereby interfering with the progress of task implementation. Unclear requirements are often associated with ambiguous scope and objectives, which lead to outcomes that are unexpected by the crowdsourcer (Keil et al. 2013). Uncertainty around tasks is also negatively correlated with crowdsourcing performance (Schenk & Guittard 2009). Considerable time and effort should be invested to analyze the task structure, which negatively influences the efficiency of task completion. Thus, we propose the following hypothesis.

H2: Technical subsystem risk negatively affects crowdsourcing performance.

Social and technical subsystem risks supposedly affect performance negatively. However, various risk types display different importance levels. Social subsystem risk, including people-related risks, influences performance more significantly than technical subsystem risk because tasks are directly performed by people (Kappelman et al 2006). In the crowdsourcing context, Franklin et al. (2011) suggested that the relationship between crowdsourcer and crowdsourcee is particularly significant because such a relationship is very complicated. The number of sponsors and crowd workers with diverse backgrounds increases the uncertainty of the social environment of crowdsourcing, which strengthens the negative influence of social subsystem risk on performance (Kannangara & Uguccioni 2013). Crowdsourcer participation is crucial to the quality of outcomes, but technical subsystem risk can be mitigated gradually by crowd workers (Rai et al. 2009). For example, continually undertaking crowdsourcing tasks can exercise the ability of an individual, and enables a crowdsourcee to acquire new knowledge and skills. Therefore, social subsystem risk is more significant than technical subsystem risk in crowdsourcing. Thus, we propose the following hypothesis.

H3: The negative relationship between social subsystem risk and crowdsourcing performance is stronger than that between technical subsystem risk and crowdsourcing performance.

We posit that technical subsystem risk strengthens the negative effect of social subsystem risk on crowdsourcing performance. High levels of technical complexity can amplify the inability of a crowdsourcee, and generates a more negative effect on performance. Requirement risk serves as a catalyst to intensify the negative effect of relationship risk (Liu et al. 2010). Unclear and conflicting requirements deteriorate the relationship between crowdsourcer and crowdsourcee, which further reduces crowdsourcing performance. Task risk also enhances the negative effect of crowdsourcer risk. In the simultaneous presence of complicated tasks and the lack of cooperation from a crowdsourcer, crowd workers find that determining contents and accomplishing tasks increase in difficulty. Overall, high levels of technical subsystem risk expand the negative impact of social subsystem risks on crowdsourcing performance. Thus, we propose the following hypothesis.

H4: High levels of technical subsystem risk enhance the negative effect of social subsystem risk on crowdsourcing performance.

Our model comprises three control variables (i.e., crowdsourcing arrangement, task type, and number of participants), that may influence performance. Crowdsourcing arrangement refers to whether a task is performed onshore (i.e., domestic crowdsourcing task) or offshore (i.e., crowdsourcing task comes from foreign countries). Crowdsourcing performance may also vary across different task types. Number of participants reflects the size and complexity of the crowdsourcing task.

4 RESEARCH METHODOLOGY

4.1 Data Collection and Validation

Quantitative data were collected from crowd participants registered in Zhubajie (www.zhubajie.com), the leading crowdsourcing platform in China. To date, over 10 million crowd participants have provided services in this platform. Zhubajie also has an international website (http://www.witmart.com/), which enables firms and individuals from foreign countries to initiate tasks. Therefore, Zhubajie is an ideal platform to collect quantitative data. We posted our formal electronic questionnaire and launched a crowdsourcing task on Zhubajie. The task required crowd participants to respond to the questionnaire by answering a series of questions associated with risk and performance based on the recent completed crowdsourcing task of the participants. The questionnaire should be answered seriously, and the tasks that the respondents selected should be accomplished within one month to overcome recall issues. Furthermore, each participant was awarded 8 RMB if they successfully responded to the questionnaire. A total of 187 responses were received within one month. However, some responses were incomplete or perfunctory. Hence, 24 questionnaires were eliminated, leaving 163 valid responses. The IP address of each respondent was also checked in case a respondent submitted more than two questionnaires. Table 1 presents the sample demographics.

Characteristic	Range	Frequency	Percentage
Age	< 20 years	7	4.29%
	20–30 years	127	77.91%
	30–40 years	27	16.56%
	> 40 years	2	1.23%
Working mode	Full-time	35	21.47%
	Part-time	128	78.53%
Gender	Male	113	69.33%
	Female	50	30.67%
Education	High school or less	16	9.82%
	Junior college	40	24.54%
	Undergraduate	96	58.9%
	Postgraduate	11	6.75%

Table 1. Sample demographics.

Harman's single-factor test was conducted to examine common method bias (Podsakoff & Organ 1986). All independent and dependent variables were included in the analysis. The results indicated that more than one factor was presented, and the most covariance that a single factor could consider was lower than 30%. Thus, common method issues were insignificant in our samples.

4.2 Constructs and Measures

The measures for all the constructs in this study were adapted from extant instruments in literature. We also modified these measures from prior research to fit our study. Specifically, the measures of crowdsourcer, crowdsourcee, complexity, and requirement risks were adopted from Wallace et al. (2004). The relationship risk items were based on the scales developed by Ikediashi et al. (2012) and John et al. (2014). The scales of the task risk were adapted from Liu and Li (2012) and Topi et al. (2005). The performance items were adopted from Mao et al. (2008) and Wallace et al. (2004). A five-point Likert scale was adopted to measure the risk and performance. For the control variables, categorical scales were used to measure crowdsourcing arrangement (onshore and offshore), task type (software development, product design, knowledge co-creation, media, and others), and number of participants (1, 2–5, 6–10, 10–20, >20). All the items and constructs are listed in Table 2.

5 RESULTS

5.1 Measurement Model

The partial least squares (PLS) method was employed to analyze the measurement model. PLS can maximize the explained variance while requiring only a small sample size (Gefen et al. 2011). Therefore, SmartPLS 2.0 was used to test both measurement model and corresponding hypotheses.

Based on the four criteria specified by Jarvis et al. (2003) and Petter et al. (2007), each construct, including crowdsourcing performance, was modeled to be reflective. Crowdsourcer, relationship, and crowdsourcee risks were modeled as first-order reflective constructs of social subsystem risk. Complexity, requirement, and task risks were modeled as first-order reflective constructs of technical subsystem risk. Social subsystem and technical subsystem risks were treated as second-order reflective constructs because their first-order constructs were somewhat interchangeable. The loadings of the first-order constructs on the corresponding second-order constructs were at an acceptable level, ranging from 0.737 to 0.887. The existence of multi-collinearity was also examined. All variance inflation factors (VIF) were lower than 1.514. Thus, multi-collinearity was insignificant in this study.

Reliability and convergent validity were first examined. Means, standard deviations (SDs), composite reliabilities (CRs), average variance extracted (AVE), and Cronbach's α of each variable were presented in Table 3. The CRs and Cronbach's α of all first- and second-order variables were all higher than 0.70. Each AVE value exceeded 0.5 (Fornell and Larcker 1981). The loadings between each item and the principle construct of the item were greater than 0.70 and were also much higher than the loadings in the other constructs, indicating that the shared variance exceeded the error one (Chin et al. 2003). Thus, the scales of the model indicated high internal consistency and reliability. Discriminant validity was then checked. The square root of AVE related to each variable exceeded the correlations between a pair of latent variables. Therefore, our model exhibited satisfactory discriminant validity. The testing results collectively indicate the high quality of the measurement model.

Construct		Measure
Social subsystem risk (SSR)	Crowdsourcer risk (CroR)	Crowdsourcer with negative attitudes toward the task
		Crowdsourcer not committed to the task
		Lack of cooperation from crowdsourcers
		Lack of crowdsourcer participation
	Relationship risk (RelR)	Conflict between crowdsourcer and crowdsourcee
		Lack of mutual trust between crowdsourcer and crowdsourcee
		Ineffective communication between crowdsourcer and crowdsourcee
		Poor relationship between crowdsourcer and crowdsourcee
	Crowdsourcee risk (CrR)	Crowdsourcee not familiar with the task
		Crowdsourcee lack specialized skills required by the task
		Inexperienced crowdsourcee
		Inadequately trained crowdsourcee
Technical subsystem risk (TSR)	Complexity risk (ComR)	Task involved the use of considerable complicated knowledge
		High level of technical complexity
		Involvement of new technology
		Involvement of immature technology
	Requirement risk (ReqR)	Incorrect requirements
		Undefined success criteria
		Conflicting requirements
		Unclear requirements
	Task risk (TasR)	Task involved numerous sub-tasks
		High interdependency among task components
		Task involved a great challenge
Crowdsourcing performance (Per)		The crowdsoucee did well enough on the task
		I believe that crowdsourcer was satisfied with the outcome of the task
		Overall, the quality of task outcome was very high
		The crowdsourcee completed the task efficiently

Table 2. Construct measurement

	CroR	RelR	CrR	ComR	ReqR	TasR	SSR	TSR	Per
Mean	2.39	2.37	2.39	2.89	2.73	2.97	2.38	2.85	3.82
SD	0.80	0.80	0.78	0.84	0.81	0.83	0.95	1.01	0.65
Cronbach's α	0.86	0.85	0.87	0.85	0.85	0.76	0.90	0.88	0.88
CR	0.91	0.90	0.91	0.90	0.90	0.86	0.92	0.90	0.91
AVE	0.71	0.69	0.71	0.69	0.69	0.68	0.68	0.63	0.73

Table 3. Descriptive statistics, reliability, and AVE.

5.2 Hypothesis Testing

We conducted hierarchical regression analysis to test our hypotheses. We developed three models in PLS following the hierarchical procedure. The initial model included the control variables only. The independent variables were then introduced in the second model, where H1 and H2 could be evaluated. This model also served as a basis to test H3. The interactive effect was tested in the third model, where H4 could be assessed. The incremental explained variance and value of *F* hierarchical, which were used to verify the significance level, could be obtained by comparing a pair of models (Carte & Russell 2003). Table 4 presents the results of hierarchical regression analysis, including the explained construct variances (R^2), standardized path coefficients, and *F* values among hierarchical models.

	Model 1	Model 2	Model 3
Block 1: Control variable			
Crowdsourcing arrangement	-0.035	-0.022	0.007
Task type	0.053	-0.001	-0.014
Number of participants	**0.224***	0.157	0.111
Block 2: Main effect			
Social subsystem risk		**-0.261****	**-0.369*****
Technical subsystem risk		-0.092	-0.046
Block 3: Interactive effect			
Social subsystem risk × Technical subsystem risk			**0.206*****
$\triangle R^2$(Crowdsourcing performance)		0.091	0.053
f^2(Effect size)		0.108	0.067
R^2(Crowdsourcing performance)	0.063	0.154	0.207
F Hierarchical		**16.888*****	**10.426*****

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 4. Hierarchical regression results.

The results (Table 4, Model 1) show that despite the insignificant influences of two control variables (i.e., crowdsourcing arrangement and task type) on crowdsourcing performance, the number of participants significantly and positively affects performance. Thus, various types of onshore and offshore crowdsourcing tasks exhibit similar performances. However, the completion of a crowdsourcing task is more likely to be successful when more participants work on the task. This result may be caused by the rich information and increasing innovative ideas developed and shared by a large group of crowd participants

Model 2 in Table 4 indicates that social subsystem risk negatively and significantly affects crowdsourcing performance, whereas the effect of technical subsystem risk on performance is insignificant. Therefore, H1 was supported but H2 was unsupported. The effect of social subsystem risk on performance ($\beta = -0.261$; $p < 0.01$) is greater and more significant than that of technical subsystem risk ($\beta = -0.092$; $p > 0.05$). We also performed a *t*-test, as suggested by Cohen et al. (2003), to further compare the two path coefficients statistically. The *t*-test result ($t = 2.38$) indicated that the effect of social subsystem risk on performance was significantly higher than that of technical subsystem risk. Therefore, H3 was supported.

Model 4 tested the interactive effect between social subsystem and technical subsystem risks on crowdsourcing performance. The interaction terms with positive and significant coefficients between social subsystem and technical subsystem risks ($\beta = 0.206$, $p < 0.001$) indicated significant effects on crowdsourcing performance. The interaction terms increased by 5.3% of the explained variance in performance. The *F* hierarchical value likewise revealed that changes in explained variance were significant. Therefore, H4 was supported.

6 DISCUSSIONS AND IMPLICATIONS

6.1 Theoretical Implications

Our research is the first attempt to provide a risk perspective to investigate the determinants of crowdsourcing performance, which is our primary contribution. The result shows that social subsystem risk significantly and negatively influences performance, whereas technical subsystem risk insignificantly affects performance. The findings of the negative and significant relationship between social subsystem risk and performance in the context of crowdsourcing conforms to our general understanding that high risks are associated with low performance. However, risks from the social and technical aspects are observed to influence performance significantly and insignificantly. This result also supports previous findings that some risk types negatively influence performance, whereas other risk types affect performance insignificantly (Wallace et al. 2004; Liu & Wang 2014).

Surprisingly, technical subsystem risk has an insignificant effect on crowdsourcing performance. One possible interpretation for the insignificant relationship between technical subsystem risk and performance could be the increased technical skills and knowledge of crowdsourcees. Crowdsourcing provides crowd participants a favorable platform to exercise the abilities of the participants. Crowd workers can accumulate abundant knowledge and experience by consistently participating in tasks. Consequently, technical subsystem risk is not perceived to be significant in crowdsourcing. Another possible reason is the self-selection process among crowd workers who are willing and able to perform tasks (Lakhani et al. 2007; Piller & Walcher 2006; Afuah & Tucci 2012). Crowd workers can evaluate their technical knowledge and ability before participating in a task and choose those tasks with low technical subsystem risk. Nevertheless, the significant relationship between social subsystem risk and performance has been determined. The empirical result demonstrates that the management of social subsystem risk is very critical. Thus, ways to supervise “people” and regulate the “social tie” of people is a major subject.

This study also compares the relative importance of the effects of the two different risks on crowd performance. Apparently, social subsystem risk exerts more significant effect on performance compared with technical subsystem risk. The results of our study support previous findings that risks associated with the social dimension are more important than risks associated with the technical dimension (Schmidt et al. 2001; Kappelman et al. 2006). This phenomenon may also be attributed to the diverse background of crowd workers and complex relationships in crowdsourcing. This finding suggests that social subsystem risk is more important, and managers should prioritize design control strategies for such a risk.

This research addresses an existing research gap by elaborating on the joint effect of social subsystem and technical subsystem risks on performance. According to previous literature, technical dimension supposedly has diverse roles in moderating the relationship between social dimension and performance. This study has empirically demonstrated the complementary effect of social and technical dimensions in the crowdsourcing context. Technical subsystem risk particularly enhances the negative effect of social subsystem risk on crowdsourcing performance. This result also supports the risk-based view that performance is worse in the presence of various risk types (Wallace & Keil 2004). In addition, although technical subsystem risk is insignificantly associated with performance, it still indirectly influences performance by interacting with social subsystem risk. Thus, the mitigation of technical subsystem risk remains significant in managing crowdsourcing tasks, especially those that largely depend on technology (e.g., information technology crowdsourcing tasks).

6.2 Managerial Implications

Identifying approaches to effectively manage risks is a major concern of managers in various areas, and crowdsourcing is not exempted. This research provides managers the following practical implications. First, given that risks negatively influence the crowdsourcing performance, crowdsourcers should master the approach of identifying risk sources, as well as further manage and mitigate risks more effectively. Intensive crowdsourcer participation is beneficial for the successful completion of tasks (Rai et al. 2009). During task execution, crowdsourcers should play an active role in mitigating crowdsourcer risk. Crowdsourcers should not simply post a task on crowdsourcing platforms with descriptions of requirements and rewards. Appropriate communications with crowd workers are also essential to maintain a positive relationship. Furthermore, crowdsoucers should provide basic guidelines for crowd workers, clearly articulate the content and goals of the task, and determine complete and accurate requirements.

Second, crowdsourcers should focus greatly on those risks that are more dangerous to performance. According to our results, compared with technical subsystem risk, social subsystem risk exerts a greater negative effect on crowdsourcing performance. Thus, ways to identify and mitigate social subsystem risk should be emphasized. Crowdsourcers should be proactive in exchanging information with crowd workers. Crowdsourcers can also develop positive relationships with crowdsourcees and establish a favorable trust mechanism (Choudhury & Sabherwal 2003).

Third, considering that social subsystem risk involves not only crowdsourcers, but also crowd workers, collaborating will be beneficial for both parties to reduce risks. On one hand, each side should reduce risks associated with both parties. A crowdsourcer should be active during the execution phase. Crowd workers should continue learning about new technology and knowledge to enhance their abilities. They should also continually participate in crowdsourcing tasks. Only through this way can the knowledge of crowdsourcees be better applied in accomplishing tasks. Furthermore, both crowdsourcer and crowdsourcee should maintain positive interactions with each other to minimize misunderstandings. On the other hand, each side should mitigate risks associated with the other party. For example, crowdsoucers can provide basic guidelines for crowd workers to assist in mitigating task risks. Crowdsourcers can also positively communicate with crowdsourcees to understand the requirements of crowdsourcers and the difficulty of completing tasks. Crowd workers can share ideas regularly with crowdsourcers.

Fourth, managers should not only concentrate on reducing social-related risks but also pay attention to the uncertainty embedded within the technical environment. A possible condition exists, where performance is still poor although social subsystem risk is reduced. The reason may be attributed to the existence of technical subsystem risk, which intensifies the negative effect of social subsystem risk on performance. Therefore, crowdsourcers should develop systematic risk management strategies that consider both risk dimensions.

7 CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

This research is an early attempt to examine the risk–performance relationship in the context of crowdsourcing. By integrating socio-technical theory and risk-based view, this study investigates the influence of social subsystem and technical subsystem risks on crowdsourcing performance. Empirical results demonstrate that social subsystem risk negatively influences crowdsourcing performance, whereas technical subsystem risk affects the performance insignificantly. The negative effect of social subsystem risk on performance is stronger than that of technical subsystem risk. These findings reveal that different types of risks play diverse roles in affecting performance. Moreover, we provide novel knowledge to existing literature by empirically indicating that different risk types interact with one another to influence performance. Technical subsystem risk particularly enhances the negative effect of social subsystem risk on performance. Therefore, crowdsourcers should develop systematic but different risk management strategies to mitigate the two risk types.

This study has several limitations. First, regardless of our best attempt to obtain additional samples, the sample used in this research is relatively small. Considerable statistical power may be gained with a larger sample size. Second, a matched-pair survey was not performed. Evaluating crowdsourcing risks and performance through different parties would be more appropriate. Third, the data used to analyze this study were collected from a single crowdsourcing platform (i.e., Zhubajie). This issue may limited the generalizability and applicability of this research. Moreover, this platform may have developed several unique rules, regulations, and operational procedures, which may have generated different types and levels of risks compared with other crowdsourcing platforms. Including more crowdsourcing platforms in our samples will be necessary in future research. Finally, our survey was conducted in China, and respondents from other countries may perceive risks differently. Further investigations are necessary to determine whether the model can be generalized into different countries.

There are a few directions for future research based on our findings. First, future research can investigate the effects of risks in a more granular level and examine how the six categories of risk developed in this study influence crowdsourcing performance. Different risks may pose various effects on performance. Second, given that social subsystem risk negatively influences performance while technical subsystem risk strengthens such a negative effect, controlling these two risks in the crowdsourcing context is significant. Future research can design appropriate risk mitigation strategies and approaches to manage such risks. Third, the different influences of risks on performance between onshore and offshore crowdsourcing is worth exploring. Risks involved in offshore crowdsourcing task may differ from onshore crowdsourcing task because the problem of cultural conflicts and communication barriers may arise in offshore crowdsourcing (Liu & Wang 2014). Finally, future research can examine the risk–performance relationship from other perspectives (e.g., crowdsourcer). The risk perceptions of different stakeholders may vary and provide additional insights into the management of crowdsourcing risks.

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References

Afuah, A. and Tucci, C.L. (2012). Crowdsourcing as a solution to distant search. Academy of Management Review, 37 (3), 355-375.

Aundhe, M.D. and Mathew, S.K. (2009). Risks in offshore IT outsourcing: A service provider perspective. European Management Journal, 27 (6), 418-428.

Borst, I. (2010). Understanding Crowdsourcing: Effects of Motivation and Rewards on Participation and Performance in Voluntary Online Activities. ERIM Electronic Series Portal, EPS-2010-221-LIS.

Bostrom, R.P. and Heinen, J.S. (1977). MIS problems and failures: A sociotechnical perspective—Part I: The causes. MIS Quarterly, 1(3), 17-32.

Carte, T. A. and Russell, C. J. (2003). In pursuit of moderation: Nine common errors and their solutions. MIS Quarterly, 27(3), 479-501

Chin, W.W., Marcolin, B.L. and Newsted, P.R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. Information Systems Research, 14(2), 189-217.

Choudhury, V., and Sabherwal, R. (2003). Portfolios of control in outsourced software development projects. Information Systems Research, 14(3), 291-314.

Cohen, J., Cohen, P., West, S.G. and Aiken, L.S. (2003). Applied Multiple Regression/Correlation Analysis for Behavioral Sciences, Lawrence Erlbaum Associates. Mahwah, NJ.

De Bakker, K., Boonstra, A. and Wortmann, H. (2010). Does risk management contribute to IT project success? A meta-analysis of empirical evidence. International Journal of Project Management, 28(5), 493-503.

Estellés-Arolas, E. and González-Ladrón-de-Guevara, F. (2012). Towards an integrated crowdsourcing definition. Journal of Information Science, 38 (2), 189-200.

Fornell, C. and Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18, 39-50.

Franklin, M. J. Kossmann, D. Kraska, T. Ramesh, S. and Xin, R. (2011). CrowdDB: Answering queries with crowdsourcing. In Proceedings of the 2011 ACM SIGMOD International Conference on Management of data, 61-72, ACM.

Gefen, D., Rigdon, E.E. and Straub, D. (2011). An update and extension to SEM guidelines for administrative and social science research. MIS Quarterly, 35(2), iii-xiv.

Hong, Y. and Hartley, J.L. (2011). Managing the supplier–supplier interface in product development: The moderating role of technological newness. Journal of Supply Chain Management, 47 (3), 43-62.

Howe, J. (2006). The rise of crowdsourcing. Wired Magazine, 14 (6), 1-4.

Howe, J. (2008). Crowdsourcing: Why the power of the crowd is driving the future of business. New York, NY, USA: Crown Publishing Group.

Ikediashi, D.I., Ogunlana, S.O., Boateng, P. and Okwuashi, O. (2012). Analysis of risks associated with facilities management outsourcing: A multivariate approach. Journal of Facilities Management, 10 (4), 301-316.

Jarvis, C.B., MacKenzie, S.B. and Podsakoff, P.M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. Journal of Consumer Research, 30 (2), 199-218.

John, St. J., Guynes, C. S. and Vedder, R. (2014). The client–vendor offshore relationship: success

factors. Information Systems Management, 31 (2), 120-125.
Khan, K., Qadri, S., Ahmad, S., Siddique, A.B., Ayoub, A. and Saeed, S. (2014). Evaluation of PMI's risk management framework and major causes of software development failure in software industry. International Journal of Scientific & Technology Research, 3 (11), 120-124.
Kannangara, S.N. and Uguccioni, P. (2013). Risk management in crowdsourcing-based business ecosystems. Technology Innovation Management Review, 3 (2), 32-38.
Kappelman, L.A., McKeeman, R. and Zhang, L. (2006). Early warning signs of IT project failure: The dominant dozen. Information Systems Management, 23 (4), 31-36.
Keil, M., Rai, A. and Liu, S. (2013). How user risk and requirements risk moderate the effects of formal and informal control on the process performance of IT projects. European Journal of Information Systems, 22 (6), 650-672.
Kittur, A. (2010). Crowdsourcing, collaboration and creativity. ACM Crossroads, 17 (2), 22-26.
Kittur, A., Nickerson, J.V., Bernstein, M., Gerber, E., Shaw, A., Zimmerman, J. and Horton, J. (2013). The future of crowd work. In Proceedings of the 2013 conference on Computer supported cooperative work, 1301-1318, ACM.
Lakhani, K.R., Jeppesen, L.B., Lohse, P.A. and Panetta, J.A. (2007). The value of openness in scientific problem solving. Working paper, Harvard Business School, Boston.
Li, K. and Wieringa, P.A. (2001). Structured operation environment and perceived complexity in human supervisory control. Asian Journal of Control, 3 (3), 181-189.
Liu, P. and Li, Z. (2012). Task complexity: A review and conceptualization framework. International Journal of Industrial Ergonomics, 42 (6), 553-568.
Liu, S. and Deng, Z. (2015). How environment risks moderate the effect of control on performance in information technology projects: Perspectives of project managers and user liaisons. International Journal of Information Management, 35(1), 80-97.
Liu, S. and Wang, L. (2014). Understanding the impact of risks on performance in internal and outsourced information technology projects: The role of strategic importance. International Journal of Project Management, 32 (8), 1494-1510.
Liu, S., Zhang, J., Keil, M. and Chen, T. (2010). Comparing senior executive and project manager perceptions of IT project risk: a Chinese Delphi study. Information Systems Journal, 20(4), 319-355.
Mao, J.Y., Lee, J.N. and Deng, C.P. (2008). Vendors' perspectives on trust and control in offshore information systems outsourcing. Information & Management, 45 (7), 482-492.
Mason, W. and Watts, D.J. (2009). Financial incentives and the performance of crowds. ACM SIGKDD Explorations Newsletter, 11 (2), 100-108.
Morris, R.R., Dontcheva, M. and Gerber, E.M. (2012). Priming for better performance in microtask crowdsourcing environments. IEEE Internet Computing, 16 (5), 13-19.
Morris, R.R., Dontcheva, M., Finkelstein, A. and Gerber, E. (2013). Affect and creative performance on crowdsourcing platforms. In Proceedings of the international conference on affective computing and intelligent interaction, 250-255, Geneva.
Nakatsu, R.T. and Iacovou, C.L. (2009). A comparative study of important risk factors involved in offshore and domestic outsourcing of software development projects: A two-panel Delphi study. Information & Management, 46(1), 57-68.
Oh, J. and Rhee, S.K. (2008). The influence of supplier capabilities and technology uncertainty on manufacturer-supplier collaboration: A study of the Korean automotive industry. International Journal of Operations & Production Management, 28 (6), 490-517.

Petter, S., Straub, D. and Rai, A. (2007). Specifying formative constructs in information systems research. MIS Quarterly, 31 (1), 623-656.

Piller, F.T. and Walcher, D. (2006). Toolkits for idea competitions: A novel method to integrate users in new product development. R&D Management, 36 (3), 307-318.

Podsakoff, P.M. and Organ, D.W. (1986). Self-reports in organizational research: Problems and prospects. Journal of Management, 12 (4), 531-544.

Rai, A., Maruping, L.M. and Venkatesh, V. (2009). Offshore information systems project success: the role of social embeddedness and cultural characteristics. MIS Quarterly, 33 (3), 617-641.

Robertson, S., Vojnovic, M. and Weber, I. (2009). Rethinking the ESP game. In Proceedings of the 27th International Conference Extended Abstracts on Human Factors in Computing Systems, 3937-3942, New York, USA.

Rogstadius, J., Kostakos, V., Kittur, A., Smus, B., Laredo, J. and Vukovic, M. (2011). An assessment of intrinsic and extrinsic motivation on task performance in crowdsourcing markets. In Proceedings of the 5th International AAAI Conference on Weblogs and Social Media, 321-328, Barcelona, Spain.

Schenk, E. and Guittard, C. (2009). Crowdsourcing: What can be outsourced to the crowd, and why. In Workshop on Open Source Innovation, Strasbourg, France.

Schmidt, R., Lyytinen, K. and Mark Keil, P. C. (2001). Identifying software project risks: An international Delphi study. Journal of Management Information Systems, 17(4), 5-36.

Spears, J.L. and Barki, H. (2010). User participation in information systems security risk management. MIS Quarterly, 34(3), 503-522.

Taylor, H. (2007). Outsourced IT projects from the vendor perspective: different goals, different risks. Journal of Global Information Management (JGIM), 15(2), 1-27.

Topi, H., Valacich, J. S. and Hoffer, J. A. (2005). The effects of task complexity and time availability limitations on human performance in database query tasks. International Journal of Human-Computer Studies, 62(3), 349-379.

Trist, E.L. (1981). The Sociotechnical Perspective in Perspectives on Organization Design and Behavior, 19-75, Wiley, New York.

Wallace, L. and Keil, M. (2004). Software project risks and their effect on outcomes. Communications of the ACM, 47(4), 68-73.

Wallace, L., Keil, M. and Rai, A. (2004). How software project risk affects project performance: An investigation of the dimensions of risk and an exploratory model. Decision Sciences, 35(2), 289-321.

Wexler, M. N. (2011). Reconfiguring the sociology of the crowd: Exploring crowdsourcing. International Journal of Sociology and Social Policy, 31(1/2), 6-20.

Zheng, H., Li, D. and Hou, W. (2011). Task design, motivation, and participation in crowdsourcing contests. International Journal of Electronic Commerce, 15(4), 57-88.

Zhu, H., Djurjagina, K., Leker, J. (2014). Innovative behaviour types and their influence on individual crowdsourcing performances. International Journal of Innovation Management, 18(6), 18p.