CRANFIELD UNIVERSITY

BINXIN ZHU

STUDY ON INCENTIVE MECHANISMS OF SMES CROWDSOURCING CONTEST INNOVATION

SCHOOL OF WATER, ENERGY AND ENVIRONMENT
PhD in Design

PhD
Academic Year: 2018 - 2021

Supervisor: Leon Williams
Associate Supervisor: Paul Lighterness
February 2021

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This thesis is submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy
(NB. This section can be removed if the award of the degree is based solely on examination of the thesis)

ABSTRACT

Dealing with insufficient resources is a common challenge yet practical reality for many project managers working within SMEs. With the rise of Web 2.0, crowdsourcing contest innovation (CCI) it is now possible for project managers to use online platforms as a way to collaborate with external agents to fill this resource gap and thus improve innovation. This research uses agent-based modelling to prognosticate the efficacy of crowdsourcing contest innovation with a particular focus on the project manager 'seeker' within an SME initiating competitive crowdsourced contest teams made up of individual 'solver' participants. The contribution of knowledge will benefit the open innovation community to better understand the main motivational incentives to obtain maximum productivity of a team with limited project management resources.

In pursuit of this, the social exchange theory is challenged, this thesis explores the motivation factors that influence solvers to participate in SMEs CCI from the perspectives of benefit perception and cost perception. The results found that non-material factors such as knowledge acquisition and sharing, reputation can stimulate solvers to participate in SMEs CCI more than material (physical money) rewards. Meanwhile, risks such as intellectual property risks and waste of resources are significant participation obstacles. Based on this, the principal-agent theory is used to design the models of team collaboration material incentive mechanism, dynamic reputation incentive mechanism and knowledge sharing incentive mechanism, and the performance of each incentive mechanism is analysed.

At last, according to the principles of sample selection, Zbj.com, the China's most successful crowdsourcing platform of which the main clients are SMEs, is chosen as the research object, and the effectiveness of the incentive mechanisms designed in this thesis is verified. It is found that the material and non-material incentives have been partially applied on the platform, and the explicit, implicit and synergistic effects of incentives are preliminarily achieved. According to the research results, it is suggested that the guarantee measures of the incentive mechanisms should be further developed, such as optimising pricing services and refining task allocation rules.

Keywords: participation motivation, incentive mechanism design, incentive effectiveness

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LIST OF ABBREVIATIONS

SMEs	Small and Medium-Sized Enterprises
CCI	Crowdsourcing Contest Innovation
R&D	Research and Development
P&G	Procter & Gamble
et al.	Et Alia
aka	Also Known As
PQDD	Proquest Digital Dissertation
PAM-ISC	Post-Acceptance Model of IS Continuance
IS	Information System
SS-Model	Single-Requester Single-Bid Model
SM-Model	Single-Requester Multiple-Bid Model
MM-Model	Multi-Requester Multiple-Bid Model
TR	Team Total Performance
NR	Individual Performance
NKS	Non-Knowledge-Sharing Incentive Mechanism Model
KS	Knowledge-Sharing Incentive Mechanism Model
i.e.	Id Est
C.R.A.A.P	Currency, Relevance, Authority, Accuracy and Purpose
SDT	Self-Determination Theory
IPR	Intellectual Proper Right
BBS	Bulletin Board System
IP	Intellectual Property
MT	Material
KAS	Knowledge Acquisition and Sharing
RT	Reputation
SB	Social Belonging
TC	Task Complexity
WOR	Waste of Resource
BP	Benefit Perception
CP	Cost Perception
PW	Participation Willingness
PU	Platform Usability
CPB	Continuous Participating Behaviour
CR	Composite Reliability
AVE	Average Variance Extracted
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root Mean Square Residual

s.t.	Subject To
IC	Incentive Compatibility Constraints
IR	Individual Rationality Constraints
IM	Instant Message
KKT	Karush-Kuhn-Tucker
KMRW	Kreps-Milgrom-Roberts-Wilson
IT	Internet Technology
HTTP	Hypertext Transfer Protocol
ID	Identity Document
NHS	National Health Service
APP	Application

1 OVERALL RESEARCH INTRODUCTION

1.1 Background

1.1.1 From Open Innovation to Crowdsourcing Innovation

With the development of the *knowledge economy* (Powell and Snellman, 2004) and the fierce competition among enterprises caused by economic globalisation, the traditional “closed” innovation model that completely relies on the enterprise’s own resources has been unable to meet the rapidly changing market demand. More companies rely on external resources and collaboration, and the characteristics of open innovation are becoming more obvious (Chesbrough, Vanhaverbeke and West, 2008; Bogers, Chesbrough and Moedas, 2018). Open innovation enables enterprises to make their customers, suppliers, research institutions, and even competitors as innovation sources.

According to Marjanovic, Fry and Chataway (2012), open innovation can be divided into three modes (as shown in Figure 1- 1): open source innovation, outsourcing, and crowdsourcing. The main features of each mode are: (1) open source innovation: the ‘solvers’ and ‘seekers’ are not completely distinguished, and there is no clear ownership of innovation achievements (Piazza *et al.*, 2019); (2) outsourcing: both the compensating contributors and who will be compensated is made clear at the outset of the relationship; (3) crowdsourcing: it is not known in advance who will be compensated. In addition, crowdsourcing is often deployed when there is uncertainty as to whether or not there is an answer to a challenge and/or where it might come from, and where problems are too high-risk (or costly) to address in-house. Hence, compared with open source innovation and outsourcing, the seekers are more willing to adopt crowdsourcing as it is comparatively more flexible and less risky.

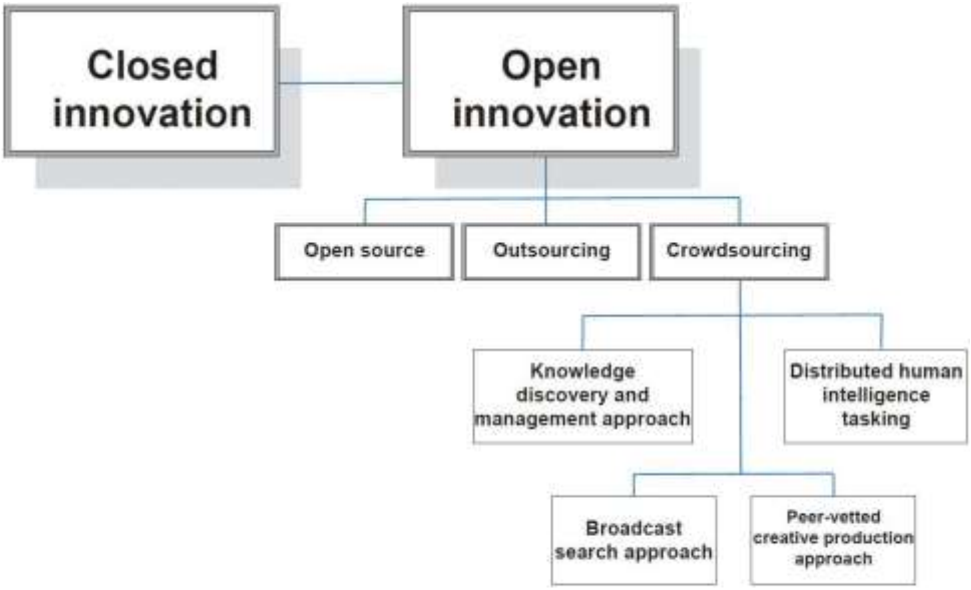

Figure 1- 1 Different types of "open innovation": open source, outsourcing and crowdsourcing

Source: Marjanovic, Fry and Chataway (2012, p321)

Crowdsourcing innovation is widely regarded as an outsourcing practice, involving online public to voluntary participate in solving innovation challenges with the rise of Web 2.0 (Howe, 2006; Enrique, Raúl and Fernando, 2015). Bringing different individuals with wide geographical and cultural distribution at low cost, it fully '*taps*' the wisdom of the masses to accelerate the process of enterprise innovation while bringing more quantities and personalised solutions, thereby maximising the enterprise R&D ability and intelligence resources for problem-solving tasks (Wei *et al*., 2015). Based on the virtue of the powerful interactive functions of Web 2.0, internationally renowned enterprises such as P&G, Dell, IBM, BMW, Siemens promote the integration of crowdsourcing and innovation system to solve innovation challenges (Ye and Zhu, 2012; Elerud-Tryde and Hooge, 2014).

For example, aiming to partner with the world's most innovative minds - from individual inventors and small businesses, to Fortune 500 companies - to deliver on the company's most challenging opportunities, P&G launched the "Connect + Develop" project. P&G relies on approximately 1.5 million crowdsourced R&D personnel around the world to provide support, and R&D productivity has increased by nearly 60%, innovation costs have fallen by 20%, and direct innovation benefits have increased by more than 70%[1]. The development of Internet technology and the rise of the grassroots movement, driven by public ambition, have made crowdsourcing innovation realistic and feasible (Xia, Zhao and Li, 2015).

Boudreau and Lakhani (2013) categorised crowdsourcing innovation into: contests, collaborative communities, complementors and labour markets. They gave out the summary of these four main types of crowdsourcing (Figure 1- 2).

	PURPOSE	CHALLENGES	BEST USE
Contests	Generating high-value solutions to complex or novel problems through large-scale and diverse independent experimentation	The problem must be generalized and stripped of company-specific details	Highly challenging technical, analytical, and scientific problems; design problems; creative or aesthetic projects
Collaborative Communities	Aggregating a large number of diverse contributions into a value-creating whole	The crowd lacks the shared culture and cohesiveness of a company, making it harder to control; intellectual property can't be protected	Customer support communities; wikis; open-collaboration projects for information and software products with complementary assets inside the firm; FAQs
Complementors	Encouraging innovative solutions to users' many different problems with your core product	It can be technologically daunting to provide access to the functions and information in the core product while protecting your assets	Open operational, product, or marketing data initiatives; content mashups; apps
Labor Markets	Efficiently and flexibly matching talent to discrete tasks	Identifying which problems to farm out and who in the organization will manage the labor pool may be difficult	Well-established categories of work that can be clearly described and evaluated; human computation; repeated tasks

Figure 1- 2 Summary of the four modes of crowdsourcing

Source: Boudreau and Lakhani (2013, p64)

1.1.2 Strong Motivation of Implementing Crowdsourcing Contest Innovation by SMEs

Small and medium-sized enterprises (SMEs) are an important part of enterprises and play an essential role in advancing development and regulating stability in the process of national economic growth. According to the "UK SME Data, Statistics & Charts (Updated Feb 2020)" by Merchant Savvy, SMEs,

[1] https://www.boshanka.co.uk/web-design-articles/crowdsourcing-is-it-wise-for-crowds-or-just-for-business/#_ftn17

which are defined as businesses fewer than 250 employees, accounted for 60% of all private sector jobs in the UK, a total of 16.6 million[2]. SMEs account for the majority of businesses worldwide, particularly in developing countries. For example, in China, from 2012 to 2020, each year, there are about five million SMEs more, representing at least a ten percent year-over-year growth rate (Textor, 2021). Due to lack of innovation resources and inadequate innovation methods, SMEs comparatively have a stronger motivation for open crowdsourcing innovation than large enterprises (Wang, 2017). It is believed that the most straightforward way for SMEs to engage a crowd is to create a contest (Qiao, 2017) because of its unique features. According to Ye and Zhu (2012), the features of crowdsourcing contest is shown in Table 1-1.

Table 1-1 Features of crowdsourcing contest

Key features	Crowdsourcing contest
Problem type	Independent technical issue
Reward mechanism	Winner-takes-all
Management difficulty	Less difficult to manage, strong operability, short time span
Knowledge exploration	High requirements on the ability to explore knowledge and problem resolution within the enterprise, and good knowledge absorption effect
Application motivation of enterprises	Time saving on new product development, cost reduce, new products acceptance increase, sales increase
Ownership of intellectual property right	Intellectual property right transferred to the enterprise after the reward is paid to the winner

(summarised by the author)

Compared with large enterprises, SMEs experience a single source of innovation, difficulty in obtaining innovation resources, and have short-term innovation expectations. This matches the characteristics of crowdsourcing

[2] https://www.merchantsavvy.co.uk/uk-sme-data-stats-charts/

contest innovation (CCI) with lower capital requirements, many solvers, less difficult management, and shorter duration. Today, online platforms such as InnoCentive, Amazon Mechanical Turk and Kaggle provide CCI services. Success has been achieved and hundreds of thousands of problems are solved worldwide. In China, the most established crowdsourcing platform - Zbj.com, from its inception in 2006 to June 2019, the number of registered users on the platform reached 19 million[3]. The number of challenges and tasks released exceeded 5.5 million, and the total bonus distribution exceeded 1.9 billion RMB. It is worth noting that the majority of registered seekers is small, medium and micro enterprises of which the total number is over 7 million, and the bonuses are more than 800 million RMB, accounting for more than 40% of the total business volume of Zbj.com. And according to Similarweb.com, Zbj.com ranks 36,205th worldwide, 1,947th in China, and 146th in the industry of Computers Electronics and Technology in the world (last updated: 01 April 2021)[4].

Although CCI has broadened the innovation channels for the development of new products of SMEs, it also faces a series of challenges. For crowdsourcing platform managers, social media operators, and crowdsourcing companies themselves, the ever-shortening technology replication cycle and the fiercely competitive information content industry are risks that cannot be ignored.

At the operational level, the biggest problem encountered in the application of SMEs CCI lies in the imperfection of incentive mechanism (Zhu *et al.*, 2016):

- The “winner-takes-all” rule is the main bonus distribution scheme which exposes the solvers to a great risk of wasting resources (Van Alstyne, Di Fiore and Schneider, 2017).
- The amount of award set in CCI is obviously inferior to that of large enterprises due to inadequate innovation fund (Maiolini, 2011; Randhawa, Wilden and West, 2019).
- Too much emphasis on material rewards (Wang and Yu, 2020), and

[3] http://web.anyv.net/index.php/article-3656860
[4] https://www.similarweb.com/website/zbj.com/?competitors=zhubajie.la

neglect of growing non-material needs of solvers (Grillos, 2017).

● The lack of integrity management, especially in the absence of a comprehensive mechanism for results management, has led to intellectual property risks in CCI tasks (Qiao, 2017).

● The lack of effective means to identify the solution's quality by SMEs, results in the problem of incentives.

Due to the above reasons, it is difficult for SMEs to attract adequate high-level solvers to participate in CCI at this stage. Taking Zbj.com as an example. The average bounce rate (uncompleted rate) of SMEs CCI tasks is as high as 38.4%, and the average solvers' stay time is only 5.52 hours (far worse than that of Mechanical Turk, 13.8% and 29.10 hours). The average rate of fulfilment of the seekers' requirement on Zbj.com is less than 20% (Chen, 2016).

1.1.3 The Importance of the Incentive Mechanism of SMEs Crowdsourcing Contest Innovation

In order to enhance the attractiveness of SMEs CCI and improve the task performance, the most fundamental way is to design an effective incentive mechanism. Undoubtedly, the incentive mechanism for enterprises to publish crowdsourcing innovation tasks and for the solvers to complete the tasks is a kind of principal-agent activity in which the enterprise is the principal and the solvers are the agents. The enterprise hopes to promote the solvers to work hard through appropriate means, and the solvers wish to achieve various rewards with less effort (Zhang and Zhang, 2017). Unlike outsourcing, crowdsourcing tasks are assigned to unknow persons on the Internet with uncertain psychology and behaviour, which will strengthen the dynamics of CCI. Compared with large enterprises, SMEs have relatively limited bonuses. In addition, in response to the solvers' growing intrinsic needs of reputation, emotions, knowledge sharing and social ownership (Kosonen *et al.*, 2014), the incentive mechanism for SMEs CCI should consider the combination of material and non-material means, and fully pay attention to the solvers' psychological features and risks during the task process, rather than material means only.

In view of the above context, this thesis focuses on the following scientific questions:

(1) *What are the motivational factors that influence the solvers to participate in SMEs CCI?*

(2) *How can SMEs (or crowdsourcing platforms) design attractive incentive mechanisms for the different motivational factors of the solvers, so as to maximise the economic benefits of the solvers and optimise the performance of the innovative task of the seekers?*

(3) *In practice, how effective are the incentive mechanisms of SMEs CCI?*

1.2 Research Purpose and Significance

1.2.1 Research Purpose

The research purposes are as follows:

● Providing a comprehensive summary of the motivational factors for solvers' participation in SMEs CCI from the two dimensions: benefit perception and cost perception. In particular, this thesis tries to excavate the non-material needs that drive the solvers' innovation efforts, and to explore the paths that each factor affects the willingness to participate and the behaviour of continued participation.

● Designing incentive mechanisms for SMEs CCI combining material and non-material factors. Meanwhile, this thesis tries to use quantitative analyse to identify the important incentive indicators which can be mathematicised and analysed in theoretical models such as solvers' innovation effort input, seekers' incentive levels, crowdsourcing task performance, and economic benefits of both the seekers and solvers of various incentive mechanisms.

● Assessing the effectiveness of the designed incentive mechanisms, and their potential problems, and proposes safeguard measures to improve the incentive performance accordingly.

1.2.2 Research Significance

Theoretical significance

The rapid development of the Internet has spawned many interdisciplinary research topics, and CCI is one of them. Due to its open nature, the diversity of solvers' behaviours, the complexity of the participating motivation and the uncertainty in crowdsourcing tasks, the traditional incentive mechanism may not be applicable under the above circumstance. Based on the multi-agent participation attribute of CCI, the principal-agent theory (Jensen and Meckling, 1978) is applied to the design of material and non-material incentive mechanisms in this thesis, and various incentive indicators are discussed in depth. The findings will expand the scope of application of the principal-agent theory and deepen the theories of open innovation (West *et al.*, 2014) and incentive theory (Killeen, 1985). In addition, exploring the characteristics of CCI from the perspective of SMEs, and fully considering the risk factors caused by SMEs' shortcomings, it helps to further enrich the innovation theory of SMEs.

Practical significance

From a practical perspective, the research on the incentive mechanism for SMEs crowdsourcing innovation is of great significance to the majority of solvers. By attracting more solvers to participate in CCI tasks, SMES will have their innovation problems better solved and their business models optimise, thereby achieving innovation capabilities and enhance core competitiveness. Effective incentive mechanisms can also stimulate people's innovation genes, and then achieve the goal of "grassroots entrepreneurship and practical innovation", which has important practical significance (Yang and An, 2018).

1.3 Literature Review

Since crowdsourcing appears, academics have shown their great interest in it. The number of crowdsourcing studies is increasing, the quality of them is constantly improving, and the research fields involved are constantly expanding. Now, a detailed review of crowdsourcing innovation, participating motivation, and related incentive mechanisms is conducted based on statistical analysis.

1.3.1 Information Sources and Literature Statistics

The concept of crowdsourcing has been proposed for less than 15 years, crowdsourcing innovation is a relatively advanced topic in academia. In order to reveal the research status from a macro perspective, according to the requirements of terminology, this section collects and organises literature that appear in related terms in themes, titles or keywords. Web of Science, EBSCO, and PQDD are selected as source databases. “Crowdsourcing innovation” as well as “witkey innovation” (Chinese word for crowdsourcing innovation) (Liu, Ouyang and Lin, 2013) are used as the search term. Literature records with no direct relevance to the research topic are excluded from the results, and 3771 papers are obtained (publication date: 01/01/2006-31/12/2019). The statistical results are shown in Table 1- 2 to Table 1- 4 and Figure 1- 3 (the deadline for data collection is April 2020).

Table 1- 2 Literature statistics on crowdsourcing innovation

Database	Web of Science	EBSCO	PQDD	Total
Number	682	1976	1113	3771

As can be seen from Table 1.2, overall, the EBSCO database has the largest number of related literatures, exceeding 50% of the total. Preliminary research finds that the theme of crowdsourcing innovation is gaining increasing attention in areas such as management and computer information science.

The analysis of the time of publication of the results can clearly reflect the development trend of research in this field. By categorising the retrieved results of crowdsourcing innovation by year, the results shown in Table 1- 3 are obtained.

Table 1- 3 Year distribution of crowdsourcing innovation related research

Database Year	Web of Science	EBSCO	PQDD	Total
2006	0	0	0	0
2007	1	4	0	5
2008	0	3	2	5
2009	6	19	8	33
2010	7	25	14	46
2011	18	64	31	113
2012	29	187	45	261
2013	37	219	79	335
2014	54	228	65	347
2015	98	209	74	381
2016	105	267	82	454
2017	117	277	254	648
2018	105	245	246	596
2019	105	229	213	547
Total	682	1976	1113	3771

Table 1- 3 shows that it was not until 2011 that the number of publications exceeded 100 each year, and then the number increased year by year. Taking the Web of Science database as an example, the development of this topic can be roughly divided into the following 3 stages (as shown in Figure 1- 3). 2008-2010 is the initial stage; 2010-2017 is the rapid development stage and 2017-2019 is the steady development stage. The research results in the initial stage mainly come from Portugal, Germany and the United States. These documents are widely regarded as 'go-to' documents of crowdsourcing innovation, which laid the knowledge base for its subsequent research. From 2010 to 2017, research results in the field showed explosive growth. The number of papers published in 2017 reached a peak, approaching over 110 for the first time. Although the number of publications has stabilised in the third stage, it can be found that crowdsourcing innovation is gradually becoming a research focus in the field of innovation management.

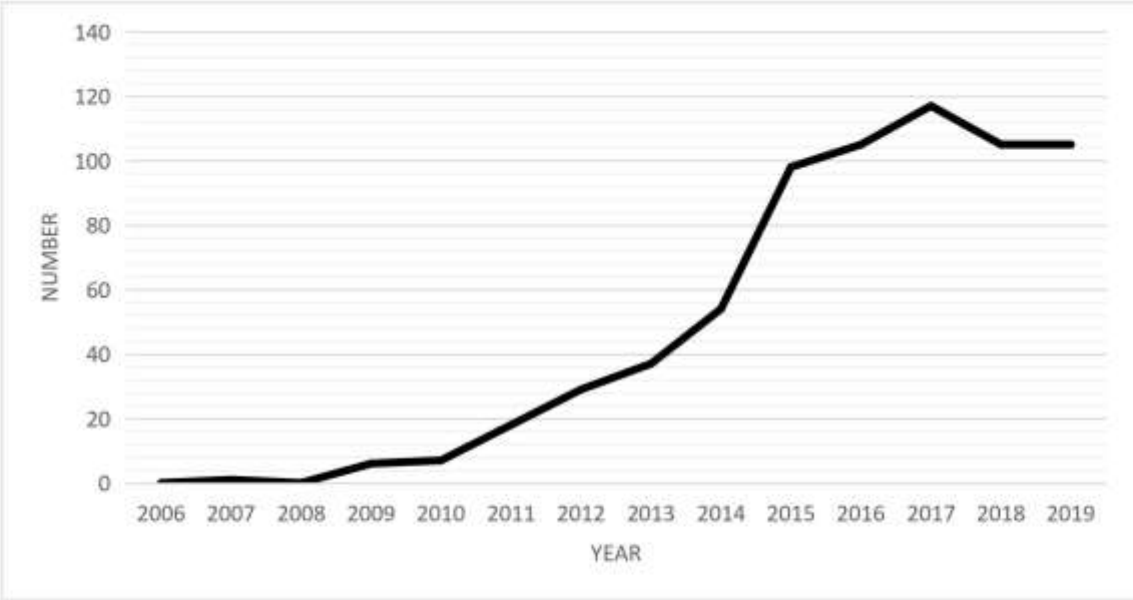

Figure 1- 3 The year distribution curve of crowdsourcing innovation related papers in Web of Science

After the analysis of the year distribution, the related research is classified by literature types shown in Table 1-4.

Table 1-4 Distribution of types of literature related to crowdsourcing innovation

Type	Web of Science	Type	EBSCO	Type	PQDD
Article	407	Academic Journals	985	Wire Feeds	563
Proceeding Paper	218	Magazines	231	Scholarly Journals	228
Review	33	Trade Publications	107	Trade Journals	76
Editorial Material	12	Dissertations	18	Conference Papers & Proceedings	70
Book Chapter	4	Reports	7	Magazines	33
Early Access	3	News	5	Books	2
Meeting Abstract	3	Books	4	Dissertations & Theses	1
Book Review	2	Reviews	1	Reports	1
Others	0	Others	618	Others	139
Total	682	**Total**	1976	**Total**	1113

Obviously, the research is mainly journal papers and conference papers, accounting for more than 77%. This shows that the current topic of crowdsourcing innovation has attracted the attention of scholars. But, the number of book, review and dissertation is comparatively small, which indicates that even though crowdsourcing innovation has become an hotspot among scholars, the research is not yet systematic and needs to be further developed, So, from the above analysis, it reflects the value of this thesis at some extent. Next, the term “crowdsourcing innovation incentive” is used to conduct a literature search. Only 132 related publications are found in Web of Science, EBSCO, and PQDD (publication date: 01/01/2006-31/12/2019) and they are mainly focused on the motivation of solvers’ participation in virtual communities, incentive strategies, incentive mechanisms and incentive design. Therefore, in the following, it is going to first sort out the connotation and application mode of crowdsourcing innovation, and then further summarise participating motivation of crowdsourcing innovation and its incentive mechanism.

1.3.2 Research on the Connotation of Crowdsourcing Innovation

The connotation of crowdsourcing innovation includes its definition, main elements and models, as well as the connection and differences between various models.

<u>Definition of crowdsourcing innovation</u>

At present, the basic definition of crowdsourcing recognised by scholars comes from Howe’s article “The Rise of Crowdsourcing”. Howe (2006) believed that crowdsourcing refers to outsourcing the work traditionally done by internal employees or external contractors to a large group with no clear boundaries. scholars gave out the definition of crowdsourcing innovation from their own background. Brabham (2010) pointed out that crowdsourcing is a new model that can gather talents and use their wisdom while reducing cost and time. Enrique and Guevara (2012) proposed that crowdsourcing means a multi-person online activity where the initiator can be an individual, a public agency, a business, or even a non-profit organisation. Similarly, crowdsourcing is defined as outsourcing traditional work done by designated institutions or individuals to a non-specific distributed network public by Saxton, Oh and Kishore (2013). Hosseini *et al.* (2015) also regarded crowdsourcing as a form of outsourcing. But rather than outsourcing, they pointed out that crowdsourcing tasks do not need to rely on a specific external organisation, and solvers have a wider range of sources and high efficiency.

The main elements of crowdsourcing innovation

The existing research generally agrees that crowdsourcing innovation consists of three dimensions: seeker (aka crowdsourcer), crowdsourcing platform, solver (aka crowdsourcee) (Chen, Wu and Zhang, 2013; Wei *et al.*, 2015; Xia, Zhao and Li, 2015; Fan and Zhou, 2016).

● *The seeker*

The initiator of crowdsourcing, referred as the seeker, is mainly from enterprises, scientific research institutions, universities and other organisations that have technological innovation needs. In order to achieve the integration of external resources, the seekers must continuously improve their ability to absorb and learn, to integrate innovative resources and to organise in different cultures. External resources may be lost when entering the organisation during the search process, which will hinder the knowledge transfer and absorption. In this case, sharing activities and tools are essential elements for improving the absorptive capacity of the enterprise. Meanwhile, the seekers should have the ability to disclose, acquisite and integrate in addition to their absorptive capacity (Mortara, L., Ford, S. and Jaeger, M., 2013). For example, Levi's once performed as the seeker launched a CCI task on Instagram. Levi's asked both men and women to upload images of themselves onto Instagram and tag them with #iamlevis.

● *The crowdsourcing platform*

The crowdsourcing platform is the main channel for enterprises to carry out crowdsourcing innovation. Some crowdsourcing platforms (such as The Global Innovation Outlook of IBM) are managed by the company itself and seek to promote sustainable innovation in commercial channels; meanwhile, there are also some crowdsourcing platforms (such as the InnoCentive) that are not built by the enterprise itself, but created and run by the intermediary company, which is mainly dedicated to providing innovative solutions for the enterprise (Jeppesen and Lakhani, 2010). The working process of crowdsourcing platform can be summarised as follows: when the user makes a request, it will send the request to the task solver; the solver will respond to this, and then the server will pass the response to the user (Howe, 2008). For the creative-generating platform, Jeppesen and Lakhani (2010) believed that Dell's "creative storm" is an open competition platform for product creativity. Through the research on Threadless, Brabham (2010) found that the company's main business model is to allowing customers to undertake tasks such as design, production and sales promotion, while Threadless itself only needs to carry out maintenance work on the website. The case of Threadless has now been cited by scholars to be a co-creation platform for mass production based on user design (Mukherjee *et al.*, 2018). Nowadays, there are many crowdsourcing contest platforms with different features. Some are open to the public and the submissions can be viewed by all such as "99designs", "Crowdspring", while some other CCI platforms are only open to the seeker, such as "TopCoder".

● *The solver*

The solvers come from all over the world, and they gather through the Internet and use information technology to communicate (Ye and Kankanhalli, 2017). Von Hippel put forward the concept of lead users and believed that lead users are the source of innovation (von Hippel, 1986). He pointed out that only by investigating and analysing lead users, understanding market needs, and obtaining program information, can internal personnel develop new products. Hence, lead users and product online users are also an important part of solvers (Robert *et al.*, 2019). For example, the solvers in crowdsourcing contest can be the clients of one company, such as costumers on MADE.com which launched an Ideas Hub. It enables its clients to submit their design of furniture and the best design will be made into the product for sale.

Connections and differences between crowdsourcing, outsourcing, and witkey

Outsourcing emerged in the 1980s when social production division was refined. Prahalad and Hamel (1990) first proposed the concept of outsourcing in the paper "The Core Competence of the Corporation". Scholars also give the definition of outsourcing in combination with personal understanding: Luo, Zheng and Jayaraman (2010) proposed that outsourcing helps to improve the overall efficiency and competitiveness for the enterprise, while the enterprise itself only focuses on those core, major functions or services. Feng, Li and Feng (2015) believed that traditional outsourcing refers to the task of delegating tasks to the enacting person or organisation in the form of a contract.

The similarities and differences between crowdsourcing and outsourcing are listed below:

- Both are products of the increasingly competitive market economy and the Information Age.
- Both extending the boundaries of organisations. Outsourcing organisations can extend the boundaries to their subcontractors, while crowdsourcing organisations include their crowdsourcing partners and even include every Internet user (Zhang, Zhong and Tu , 2012).
- Both make innovation no longer confined to the inside of enterprises, and enterprises begin to seek innovation capabilities, which is the biggest breakthrough in the traditional innovation model (Tu, Sun and Zhang, 2015a).
- Outsourcing emphasises a high degree of specialisation and relies on professional institutions and people. On the contrary, crowdsourcing advocates the innovation potential stimulated by social diversification and differentiation, and depends more on individual behaviour (Lisowska and Stanisławski, 2015).

As mentioned before, crowdsourcing has a different name in China: 'Witkey', which together with search engines has become the driving force of the development of the Internet. The concept of witkey was first proposed by Liu Feng in 2005. He defined witkey as a group of workers, who use wisdom and creativity in the Internet Age, to sell the value of their intangible assets on online platforms, in order to get paid for the work released by the employer (Liu, Ouyang and Lin, 2013). Shi and Zou (2009) believed that unlike other Web 2.0 applications, witkey is not an imported product, but a new generation of Internet applications rooted in China. Regarding the relationship between crowdsourcing and witkey, Meng, Zhang and Dong (2014) thought witkey is one of the constituent types of crowdsourcing. Tu, Sun and Zhang (2015b) pointed the most difference between crowdsourcing and witkey lies in the starting point: Witkey is more positioned in the mass group, while crowdsourcing is located in the organisation. The former is an individual Internet model and mainly used to solve problems in the fields of science, technology, work, life, and learning. The latter is an organisational mode that transfers the work traditionally undertaken by the internal members of an organisation or institution to the external mass group through the Internet in a free and voluntary form. Fundamentally speaking, witkey and crowdsourcing are actually referring to the same real-life phenomenon (Lin, Ouyang and Lin, 2013).

1.3.3 Research on Solvers' Motivation Factors of Participating in Crowdsourcing Innovation

An effective incentive mechanism is the primary condition for the success of crowdsourcing innovation, and the basis of the incentive mechanism is the study of solvers' participating motivation. Generally, participating motivation can be divided into internal and external ones. The former (internal motivations) mainly comes from the individual's pursuit of self-determined internal motivation, while the latter (external motivations) comes mainly from the stimulation of external economic conditions (Ryan and Deci, 2000). This thesis summarises several main motivations for mass participation in crowdsourcing innovation.

Material needs

The reason why crowdsourcing can make people excited is that people who provide ideas or labour for the seeker can get material rewards; for more professional work such as R&D, the reward may be more (Bogers, Afuah and Bastian, 2010). Organisciak (2010) explained the motivation of solvers to participate in crowdsourcing and found that when other incentives are invalid or the effect is not obvious, the incentive of money makes solvers more active in crowdsourcing. Boudreau, Lacetera and Lakhani (2011) conducted a study of users on the Topcoder, found that the most obvious motivation for mass participation in crowdsourcing contest is to receive bonuses. Zhu, Zhang and Zhang (2016) used three sets of comparative experiments and found that different monetary incentives have different adjustment effects on solvers' internal and external participation motivation.

Psychological needs

Most solvers are engaged in crowdsourcing because of their hobbies, and their purpose is often non-commercial, such as social belonging and entertainment (Bakici, 2020). Each solver is unique, and the knowledge or talent they have is valuable to other solvers. Also, solvers are eager to get the approval of others, and the greatest value that crowdsourcing brings to solvers is the satisfaction of psychological needs. Solvers can communicate and collaborate on instant messaging tools on crowdsourcing platform. Crowdsourcing platform often sets certain specific topics. Those with the same interests and hobbies communicate through the intermediary crowdsourcing platform. This is beneficial to exchange relevant experiences and make like-minded friends (Piezunka and Dahlander, 2015). Zhong, Wang and Qiu (2011) conducted the empirical analysis by post-acceptance model of IS continuance (PAM-ISC) model (Lawkobkit and Speece, 2012) and found that Chinese netizens may pay more attention to the fun of participating in the community, self-affirmation and virtual community sense.

Learning new knowledge and skills needs

Maslow (1943) pointed out that there is a strong knowledge demand in human life, that is, curiosity. Crowdsourcing has become an important source of knowledge and skill acquisition, and crowdsourcing platforms are built on the basis of knowledge creation, skill learning and interaction. Solvers can share their knowledge on the platform, discuss and communicate with each other, discover and learn the knowledge they are interested in, thus enriching their own knowledge and improving their task solving skills (Bogers, Afuah and Bastian, 2010; Ståhlbröst and Bergvall-Kåreborn, 2011).

Other motivations

In addition to the above motivations, there are some other motivations that will affect the public's participation in crowdsourcing. Xia and Zhao (2017) believed that emotional motivation is a kind of special participation motivation. Well-known companies such as P&G, IBM, Dell, and Starbucks, most solvers of their innovation tasks have strong loyalty to the brand, and in reality, are the loyal consumers. With the upgrading of product experience, the improvement of service quality and the enhancement of incentive intensity, the emotional motivation is gradually strengthened (Alnawas and Hemsley-Brown, 2018). Brabham (2010) found that the motivation of the public to participate in the crowdsourcing community also includes promotion, knowing strangers, spending leisure time and reaching out to new societies. Organisciak (2010) also found a common motivation for solvers to participate in the crowdsourcing community, that is, the entry threshold of crowdsourcing community is low, and the design of crowdsourcing community is more acceptable to them.

1.3.4 Research on Incentive Mechanisms of Crowdsourcing Innovation

Crowdsourcing innovation is an innovation behaviour involving multiple subjects with a principal-agent relationship between seekers and the solvers. Therefore, the research of incentive mechanism is mostly based on principal-agent theory.

The incentive mechanism from previous studies can basically be divided into two categories: material and non-material incentive mechanism.

Material incentive mechanism

By conducting surveys on InnoCentive, Starbucks and other crowdsourcing platforms, Zhang and Lu (2012) and Rui *et al.* (2016) pointed out that the current incentive mechanisms for crowdsourcing innovation is relatively simple and most of them are fixed bonus rewards. Tian, Deng and Fei (2016) studied the optimal reward mechanism for crowdsourcing contest. The results show that the seekers and solvers under the fixed reward mechanism cannot achieve incentive compatibility; the bidding incentive mechanism can achieve the goal of incentive compatibility.

Non-material incentive mechanism

Although the non-material motivations of mass participation in crowdsourcing innovation has been recognised by most scholars, research on non-material incentive mechanisms is not sufficient yet. Focusing on analysing the effects of different kinds of rewards to increase the number of crowdsourcing ideas submitted, Cappa, Rosso and Hayes (2019) identified the presence of a non-material reward can increase the number of participants in a crowdsourcing campaign. Zhang *et al.* (2015) considered that there is a cooperative relationship among solvers. According to the number of service platforms and the number of solvers bidding, three cooperative incentive models which are SS-Model (Single-requester Single-bid), SM-Model (Single-requester Multiple- bid) and MM-Model (Multi-requester Multiple-bid) are proposed. Gao, Hou and Huang (2015) proposed an incentive mechanism to achieve long-term solvers' participation by selecting solvers based on their location conditions.

It is worth noting that there are relatively many studies on reputation incentive mechanism. Zhang and Van Der Schaar (2012) studied a reputation-based incentive mechanism and established the utility matrix. Besides, Malandrino, Casetti and Chiasserini (2012) specifically designed a credibility-based processing and penalty mechanism for malicious defamation attacks in response to the malicious behaviour of solvers. Huang and Chen (2019) built a reputation evaluation mechanism under the big data environment in order to solve the problem of transaction fraud.

1.3.5 Research Comment

By combing the above research literatures, it is found that crowdsourcing innovation has received a lot of attention in academia. But the results of the relative research on crowdsourcing incentive mechanisms are not rich, and the research is not systematic.

● The research on the key motivation factors of solvers' participation in crowdsourcing innovation has certain defects.

Solvers' motivation is important for achieving crowdsourcing goals. However, as far as the existing research is concerned, the methods are mostly qualitative research and case analysis (Brabham, 2008; Bayus, 2013), and less attention is paid to quantitative exploration, which leads to insufficient robustness of conclusions. Besides, most studies focus on positive motivational factors (Spindeldreher and Schlagwein, 2016; Xia and Zhao, 2017; Barashev and Li, 2018), while ignoring the negative impacts of systemic risks and effort costs on participation motivation. In addition, the virtual crowdsourcing community has got a high degree of attention (Huang and Cao, 2018), but the research on the factors of crowdsourcing contest participation motivation is relatively insufficient. What's more, how to turn motivation into continuous participation is often overlooked.

● There is a lack of crowdsourcing research targeting on SMEs.

As an important part of the economy and society, SMEs urgently need to use technological innovation to promote the transformation and upgrading of enterprises. Due to the lack of funding and technical support, it is not possible to carry out innovation activities as effectively as large enterprises, and it is necessary to rely on external resources. As a result, SMEs in the future will certainly become the main body for implementing crowdsourcing innovation. Obviously, there are many differences between SMEs and large enterprises in crowdsourcing. SMEs crowdsourcing tasks, they are mainly carried out through a third-party crowdsourcing platform, which is based on a bounty contest model, the task bonus is not very high, and the protection of intellectual property rights is not enough (Zhang and Chen, 2009; Spithoven, Vanhaverbeke and Roijakkers, 2013). Existing research has not clearly classified the types of crowdsourcing enterprises, so the conclusions are general and fail to take the characteristics of SMEs CCI into consideration.

● The research on the crowdsourcing contest incentive mechanism and its guarantee system are not systematic enough.

First of all, the existing research mainly focuses on the development status and trends of crowdsourcing innovation platforms (Huang, Qin and Wu, 2015; Fan and Zhou, 2016), innovation model exploration (Ye and Zhu, 2012; Deng *et al.*, 2016) and influencing factors of solvers' participation (Meng, Zhang and Dong, 2014), the research on incentive mechanism is relatively lacking. Second, material incentives are seen as the main means to attract solvers. In fact, in SMEs CCI, due to the low bonus amount, the influence of the non-material motivations such as reputation, interest, and knowledge sharing should not be neglected. Third, the existing literature rarely considers the "winner-takes-all" feature of crowdsourcing contest, and fails to derive the winning probability of the solvers, so the conclusions are somewhat different from the actual situation. Finally, from the practice of crowdsourcing innovation, there is no mature research framework for establishing a reasonable incentive mechanism guarantee system.

Based on the shortcomings of the existing research, this thesis focuses on SMEs and tries to provide both theoretical and practical base for fully revealing the inherent operating mechanism of the crowdsourcing innovation, and clarifying the optimisation and improvement direction of this innovation model, in order to further promote the innovation of SMEs.

1.4 Research Aim and Objectives

The research aim of this thesis is to design incentive mechanisms in order to improve the performance of SMEs CCI. Three objectives are set up in order to achieve the research aim, which are shown in Figure 1- 4.

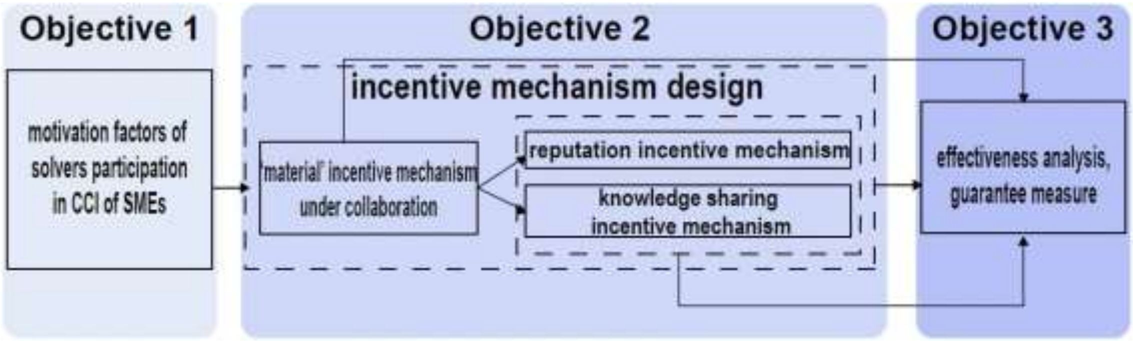

Figure 1- 4 Logical framework of research objectives

(designed by the author)

As shown in Figure 1- 4, Objective 1 is to understand the motivational factors that affect solvers to participate in CCI of SMEs. Objective 2 is the core of this thesis. Based on the result of Objective 1, trying to design incentive mechanisms accordingly. The highlight here is not only the material incentive mechanism is designed, but also the non-material factors including reputation and knowledge sharing are taken into consideration. The last objective – Objective 3 is to verify the effectiveness of the designed incentive mechanisms applied in the industries including brand design, copywriting planning, marketing promotion and e-commerce service, and to give out guarantee measures at last. The whole framework follows the pattern from simple to complex, from practice to theory to practice, forming the content closed loop.

1.5 Structure of the Thesis

This thesis is presented as a series of chapters formatted as journal papers.

<u>Chapter 1. Overall Research Introduction</u>

This chapter puts forward the research aims and objectives by introducing the realistic background and makes a detailed review of the relevant literature.

Furthermore, it introduces the research approach and structure of the thesis, puts forward the technical roadmap and summarises the innovation points.

Chapter 2. Motivation Analysis of Solvers' Participation in SMEs Crowdsourcing Contest Innovation

In Chapter 2, empirical research is conducted to study the motivation of solvers to participate in the SMEs CCI tasks based on the social exchange theory. Through data collecting and analysis from mainstream crowdsourcing platforms, the main motivation factors are classified to benefit perception and cost perception, and a conceptual model of the participation motivation and behaviour is proposed accordingly. With the usage of SPSS.22 and Mplus7, the conceptual model is analysed for reliability and validity, and the path coefficient and significance index of each motivation factor (especially material factor, reputation factor, knowledge sharing factor and various cost perception factors) on the participation motivation and behaviour are calculated. This chapter lay a theoretical foundation for the design of incentive mechanisms.

Chapter 3. Material Mechanism considering Collaboration Effect

In this part, a material incentive mechanism is designed for SMEs CCI when the tasks are complex and can be modularised. By adopting the principal agent theory, two incentive models based on team total performance (TR) and individual performance (NR) considering solvers self-interested efforts and altruistic efforts are established and solved by reverse induction method. Then, mathematical methods and computer simulation are adopted to analyse how the incentive indicators such as effort, task performance, economic benefits are influenced by the retained task volume, the solvers' risk aversion and the number of solvers, as well as the preferences of the two incentive models.

Chapter 4. Dynamic Incentive Mechanism Based on Reputation Effect

This chapter designs a dynamic incentive mechanism of two-stage CCI in the case of solvers' single participation under reputation motivation. Considering the characteristics of the "winner-takes-all" in CCI, the winning probability of each solver is calculated according the sum of its efforts and explicit reputation performance, and the reputation performance incentive model of two consecutive task stages is established. The optimal effort level, the unit performance reward, the task performance and the the seeker's economic benefit are solved by the similar methods of Chapter 3. This chapter specifically discusses the relationship between the uncertainty of explicit reputation, implicit reputation, number of solvers and above indicators, and makes a detailed comparison with the results of no reputation incentive mechanism by computer simulation using MATLAB 7.0.

Chapter 5. Knowledge Sharing Incentive Mechanism

In the view of the important non-material factor - knowledge sharing, the necessity and possibility of setting up a shared CCI community is discussed by taking into full consideration the characteristics of both cooperation and competition of the solver in this chapter. Based on the calculation of the solvers' winning probability, the non-knowledge sharing incentive mechanism model (NKS) and the knowledge sharing incentive mechanism model (KS) in crowdsourcing community considering solvers' horizontal fairness concerns are built up. By solving the models using game theory, sensitivity analysis is used to explore the impact of solver's fairness concern on the optimal incentive degree of knowledge sharing, private solution effort, knowledge sharing effort, task performance and economic benefits of both the seekers and solvers.

Chapter 6. Effectiveness Illustration and Guarantee Measures of the Incentive Mechanism of SMEs Crowdsourcing Contest Innovation

In this chapter, the effectiveness of designed incentive mechanisms is mainly analysed by qualitative research. Taking the Zbj.com as the object, and the data is collected through web crawling and large second-hand data on Zbj.com. The effectiveness of the incentive mechanism is analysed, and safeguard measures are proposed accordingly.

Chapter 7. Discussion

Based on the research results, highlighting the most significant findings of the thesis in this chapter, and the scientific questions put forward in Chapter 1 are answered in detail. Meanwhile, the limitations of this thesis and the possible refining solutions are given out at the end of this chapter.

<u>Chapter 8. Conclusions and Future Work</u>

The conclusions obtained by previous chapters are summarised in this chapter. The answers to the scientific questions of the thesis and contributions of knowledge are given out. And the future research directions/work are discussed in this section.

1.6 Methodology and Technical Roadmap

The overall technical roadmap of this thesis is shown in Figure 1-5.

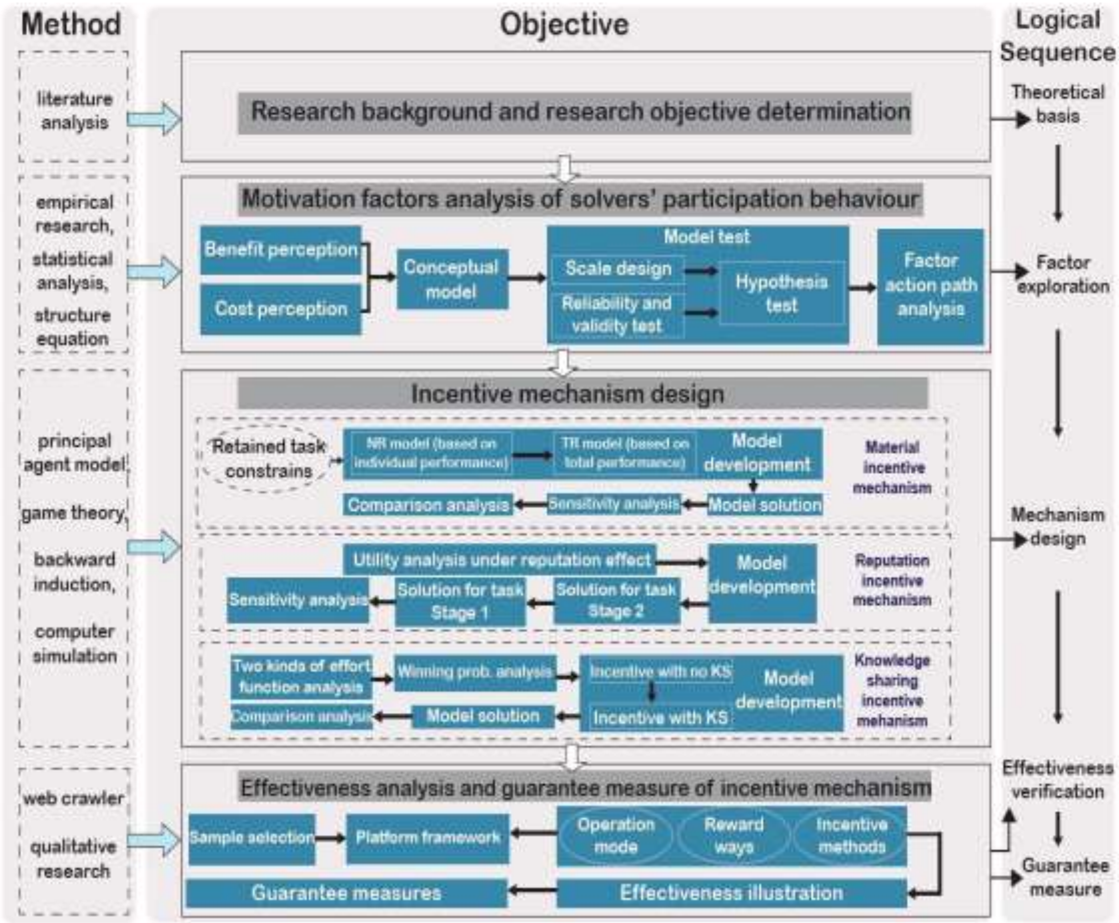

Figure 1-5 Research ideas and technology roadmap

(designed by the author)

This thesis takes the logical order between the research contents as the main line and is organised in the order of “Theoretical basis → Motivation factor analysis → Incentive mechanisms design → Effectiveness verification and safeguard measures”.

Figure 1- 5 shows the methods adopted in each section of this thesis. First, at the preparation stage, by reading a large number of relevant literatures, literature analysis is used to determine the research objectives and lay a theoretical basis for the whole research. Second, for the motivation factors exploration, empirical research, statistical analysis and structural equation model are used. Third, principal-agent model and game theory are used to establish the incentive models and backward induction is later used to solve the models. If the results are too complicated, computer simulation is going to be adopted as an auxiliary method. Last but not least, for the incentive mechanisms' effectiveness analysis, web crawling and qualitative research are used. Based on the results of the effectiveness, guarantee measures are proposed accordingly.

1.7 Innovation Points of the Thesis

The main innovation points of this thesis can be summarised as follows:

● Deepening the theory of crowdsourcing contest innovation

As the latest development stage of open innovation, crowdsourcing innovation has gradually attracted the attention of enterprises and academia. CCI is the main mode of crowdsourcing innovation in practice. However, most studies on CCI are limited to qualitative descriptions of model features, organisational processes, and practical values. Starting from the empirical research on the solvers' participation motivation, this thesis describes the operation mechanism of winner-takes-all CCI through the calculation of the solvers' winning probability. Incentive models based on performance rewards are constructed to quantify the performance value and economic value of CCI. This provides a general framework for quantitative research on CCI, thus deepening the theory of CCI.

● Exploring the motivation factors of solvers participating in SMEscrowdsourcing contest innovation

The existing crowdsourcing innovation theories rarely touch the scope of the representation of SMEs crowdsourcing innovation. In fact, SMEs have an extremely urgent desire for crowdsourcing innovation due to the constraints of internal innovation resources. However, the CCI tasks implemented by SMEs have distinctive features, such as limited rewards, high requirements for solution submission time, and high intellectual property risks. Therefore, the motivation factors of solvers participating in SMEs CCI are significantly different from those of large enterprises. Based on the social exchange theory, this thesis deeply explores these key motivation factors, and lay the basis for the constructions of incentive mechanisms. Hence, the scope of application of CCI is expanded.

● Providing a new means for studying the non-material incentive mechanism of SMEs crowdsourcing contest innovation

Most of the existing research on the incentive mechanism of crowdsourcing innovation is based on material incentives (such as monetary reward). This thesis believes that in view of the constraints of SMEs' innovation resources, the economic benefits obtained by solvers from participating in SMEs CCI are limited, and non-material motives such as reputation, emotion, and knowledge sharing cannot be ignored. Therefore, it is necessary to establish a non-incentive mechanism for SMEs CCI, or to effectively integrate non-material factors into the incentive process. It is worth noting that under the non-material incentive mechanisms, the incentive constraints of solvers will change from maximising economic benefits to maximising utility.

● Analysing the effectiveness of the incentive mechanism for SMEs crowdsourcing contest innovation

Whether the incentive mechanisms designed in this thesis can produce the expected results need to be tested by practice. The existing research on incentive mechanisms of crowdsourcing innovation mainly focuses on theoretical process design and performance deduction but lacks further exploration on their practical effects. This thesis takes Zbj.com as the object and verifying the effectiveness of designed incentive mechanism. It can be said that the logical arrangement of this thesis from participation motivation to incentive mechanism design to effectiveness test reflects the progressive thinking from practice to theory and then to practice, and interprets the closed-loop content of “from practice to practice”.

1.8 Research Publications

Zhu, B. X., Ma, Z. Q. and Li, Z. (2019) ‘Research on incentive mechanism of performances of cooperative crowdsourcing projects based on risk preference’, *Industrial Engineering and Management*, 24(3), pp. 60-68. Available at: doi/10.19495/j.cnki.1007-5429.2019.03.008.

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Huang, T., **Zhu*, B. X.** and Ma, Z. Q. (2019) ‘Research on the impact of participant's fairness preference on collaborative crowdsourcing project performance’s incentive mechanism’, *Science & Technology Progress and Policy*, 36(23), pp. 11-19. Available at: doi/10.6049/kjjbydc.2019010239.

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2 RESEARCH ON SOLVERS' PARTICIPATING MOTIVATION IN SMES CROWDSOURCING CONTEST INNOVATION

Abstract

To find out the main motivation factors of solvers participating in SMEs crowdsourcing contest innovation (CCI), empirical study is conducted by adopting the structure equation model. Firstly, by identifying and critiquing several theories that have been applied to explore solvers' participation motivation in crowdsourcing innovation, the reasons why social exchange theory is chosen as the theoretical base are explained. Second, the research hypotheses are put forward from the two aspects of benefit perception and cost perception, and the conceptual model is constructed. Third, the questionnaire survey is carried out, and research data is collected. Fourth, the structural equation model is used to conduct the empirical research.

The results show that the non-material factors such as knowledge acquisition and sharing, reputation are positively correlated with the interest perception of solvers, and the significance is higher than the material factor. Intellectual property and resource waste risk is positively related to cost perception. And platform ease of use has a significantly positive relation with continuous participation motivation. According to the research results, some suggestions are put forward on solvers' participation behaviour.

Keywords: participation behaviour, crowdsourcing contest innovation, empirical study, motivation factors

2.1 Introduction

The emergence of crowdsourcing realises the integration of enterprises and global Internet resources, which has greatly improved the innovation efficiency of enterprises. Compared with large enterprises, SMEs are in lack of R&D funds and have insufficient internal innovation capabilities (Pierre and Fernandez, 2018). They rely more on inter-organisational relationships and external networks to stay competitive and are more likely to use an open innovation approach. Research shows that the Internet is an important driving force for SMEs to innovate in today's environment, and crowdsourcing innovation will become the most promising application model for the open development of SMEs in the future (Maiolini and Naggi, 2011).

However, affected by the relatively short-term entrepreneurial goals of SMEs and the lack of access to and protection of the wisdom of people (Maiolini and Naggi, 2011), SMEs have to entrust third-party crowdsourcing platforms to conduct crowdsourcing contest innovation. Although this helps SMEs to save innovation costs, it is contrary to the needs of solvers in pursuit of social value, which not only causes a risk of waste of resources, but also reduces the motivation of solvers to participate in SMEs *crowdsourcing contest innovation* (CCI).

Previous research shows that the average number of solvers participating in a single crowdsourcing project on the Internet and the quality of solutions are far inferior to crowdsourcing tasks held by large companies such as P&G and IBM (Hao, Hou and Zheng, 2016). This indicates that in the Internet environment, how to attract more solvers to pay attention to and participate in crowdsourcing innovation activities, and actively expand the number of solvers has become an urgent problem for SMEs crowdsourcing platforms or seekers.

Only by accurately grasping solvers' participating motivations and finding the critical path that affects solvers' continuous participating behaviour, can the incentive mechanism for crowdsourcing innovation be effectively constructed and the performance of crowdsourcing innovation be maximally improved.

However, previous research on the solvers' motivation to participate in SMEs CCI is rare. Obviously, the resources invested by SMEs in CCI are far less than those of large enterprises, and solvers will experience very different benefits and risks, the motivations must be different. Also, the relevant research mainly focus on the positive factors that encourage public's participation (Baruch, May and Yu, 2016; Pinto and dos Santos, 2018; Wijekoon, Schegolev and Merunka, 2020), but ignores the impact of negative factors such as intellectual right risk on the participation motivation of solvers. In addition, according to the research of (Wang and Yu, 2020), sustainable crowdsourcing innovation is an effective method to use internal and external resources to improve the quality of enterprise innovation, and the efficiency of macro-task competitive advantage in the process of new product development in a relatively long period. In other words, the continuous participation behaviour of the solver is an important factor influencing whether the company can make full use of crowdsourcing innovation to obtain long-term high-quality innovation results. Based on the above, this chapter tries to systematically explore the motivation factors of solvers' participation and the influence path of continuous participating behaviour from the positive (benefit) and negative (cost) aspects of SMEs CCI.

2.2 Theoretical Basis

The crowd creativity might draw on social and anthropological theories applicable to groups and network cultures (Terranova, 2004), and the technologies enable crowdsourcing are not just physical, but also social, which indicates that for exploring solvers' motives in the crowdsourcing process, it is necessary to consider influencing factors comprehensively, including social norms, values and behaviours (Marjanovic, Fry and Chataway, 2012).

By reviewing a number of scholarly studies on the motivations of solvers' participating willingness and behaviour in crowdsourcing innovation, the most appropriate and cutting-edge research theoretical base that could be leveraged as part of this chapter are to be identified. To make sure the sources are verifiable, accurate, objective and authoritative, it is considered to follow the criteria – C.R.A.A.P (Currency, Relevance, Authority, Accuracy and Purpose.

Source: Writing Centre, University of Arizona[5]) to choose supportive research evidence, and their information is shown in Table 2- 1.

Table 2- 1 Basic information of selected references

Title	Author and Organisation	Publication Year	Journal Name and Impact Factor	Number of Citations
Better together—Harnessing motivations for energy utility crowdsourcing activities	Andrew Flostrand, Theresa Eriksson and Terrence E. Brown. Luleå Technical University, Royal Institute of Technology	2019	Energy Research & Social Science 4.771	4
Understanding solvers' continuance intention in crowdsourcing contest platform: An extension of expectation-confirmation model	Mengmeng Wang and Jianjun Wang. Dalian University of Technology	2019	Journal of Theoretical and Applied Electronic Commerce Research 1.901	5
Effect of crowd voting on participation in crowdsourcing contests	Liang Chen, Pei Xu and De Liu. West Texas A&M University, Auburn University, University of Minnesota Twin Cities	2020	Journal of Management Information Systems 3.949	7
Motivations of crowdsourcing contributors	Pinto, Luiz & Santos Jr, Carlos. Independent Researcher, University of Brasília	2018	Innovation & Management Review N/A	7
Solvers' participation in crowdsourcing platforms: Examining the impacts of trust, and benefit and cost factors	Ye, Hua (Jonathan) and Kankanhalli, Atreyi. The University of Auckland, National University of Singapore	2017	The Journal of Strategic Information Systems 5.231	71

As shown in Table 2- 1, the exciting research is being undertaken by scholars globally, such as Luleå Technical University, Sweden; Dalian University of Technology, China; West Texas A&M University, USA; University of Brasília, Brasília, Brazil; National University of Singapore; and The University of Auckland, New Zealand. The content of the papers is close to this thesis and most of them are published in last 5 years.

[5] https://writingcenter.uagc.edu/choosing-best-sources-and-evidence

The theories adopted in the above research are ‘self-determination theory’, ‘expectation-confirmation theory’, ‘expectancy theory’, ‘theory of planned behaviour’ and ‘social exchange theory’ (Table 2-2).

Table 2- 2 Theories used to explore motive factors of solvers' participation in crowdsourcing innovation

Main theories	Proposition	Result from representative research	Related reference
Self-determination theory	Individuals can be seen as a continuum of self-determination, and their motivation ranges from spontaneous (completely lack of self-determination) to external motivation, and then to internal motivation (complete self-determination).	nonself-determined behaviour (amotivation) → extrinsic motivation → self-determined behaviour (intrinsic motivation)	Flostrand, Eriksson and Brown (2019)
Expectation-confirmation theory	The individual's degree of satisfaction and continued participation intentions are mainly determined by two factors: initial expectations for products and services and the level of confirmation of expectations.	interaction; perceived fairness → confirmation → perceived benefits; platform trust → satisfaction → continuance intention	Wang and Wang (2019)
Expectancy theory	The reason why individuals show certain behaviours is because they are more motivated to choose this behaviour than others, and these behaviour motivations come from the individual's expectations of the behaviour results.	reliance on crowd voting → winning expectancy → participation	Chen, Xu and Liu (2020)
Theory of planned behaviour	The degree of realisation of an individual's behaviour depends on his willingness to devote himself to the action.	attitude; self-efficacy; monetary rewards; acknowledgement; fun and satisfaction; learning → intention of contribution	Pinto and dos Santos (2018)
Social exchange theory	All actions of individuals and society boil down to a kind of exchange, and the various complex social relations formed in social exchanges are also exchange relations. The way of individual behaviour is to maximise the benefits obtained from the exchange relationship and minimise the cost.	benefits (monetary reward, skill enhancement, peer reputation, enjoyment, work autonomy); costs (cognitive effort, loss of knowledge power) → participation in crowdsourcing	Ye and Kankanhalli (2017)

*To ensure scholarly rigour – it is attempted to critique the theories to access which is suitable for this chapter (*Table 2- 2*).*

Critique of: *Self-determination theory (SDT):* It represents a broad framework for the study of human motivation and assumes that individuals have an inherent desire for energies to drive their actions (Ryan and Deci, 2000b). One of the widely accepted assumptions of the theory is that motivations, based on their locus of causality (i.e. the origin) are divided into external (i.e. extrinsic) and internal (i.e. intrinsic) motivations (Ryan and Deci, 2000a). According Gagné and Deci (2005), SDT posits a self-determination continuum which ranges from amotivation (wholly lacking in self-determination) to extrinsic motivation, then to intrinsic motivation (invariantly self-determined). Flostrand, Eriksson and Brown (2019) used SDT to articulate motivations for members of the external clients to provide value to the firms through crowdsourcing activities and formulated five propositions to jointly determine how energy companies should use SDT to design crowdsourcing activities.

Critique of: *Expectation-confirmation theory:* The theory is originally used to explain the reasons of consumers' satisfaction and repurchase intention Bhattacherjee (2001). It was found out that initial expectation on a product or service and the confirmation level are the two above aspects. Based on expectation-confirmation theory, Wang and Wang (2019) built up the expectation-confirmation model to understand solvers' continuance intention in crowdsourcing contest platform and found satisfaction, perceived benefits, and platform trust are most important factors in influencing solvers' continuance intention.

Critique of: *Expectancy theory (or expectancy theory of motivation):* It proposes that an individual will behave or act in a certain way because they are motivated to select a specific behaviour over others due to what they expect the result of that selected behaviour will be (Oliver, 1974). It has been widely used to investigate work motivation (Vroom, 1964) and its application scope has been extended to the online context in recent years (Hann *et al.*, 2007). According to this theory, whether a worker puts effort on the work is mainly affected by three key emotional elements namely valence, instrumentality and expectancy. Chen, Xu and Liu (2020) adopted expectancy theory to reveal the relationship between crowd-voting reliance and participation in crowdsourcing contests.

Critique of: *Theory of planned behaviour:* It is one of the most popular theories used in studies on exploring the variables preceding the intention of individual's contribution in crowdsourcing (Pinto and dos Santos, 2018). The theory of planned behaviour is mainly focused on measuring the intention by the individual of practicing certain behaviour, that is, how willing he is and how much effort he intends to put in. As a general rule, it is understood that the more one is intended to act in a certain way, the more likely it is that this behaviour materialises (Icek, 1991). Pinto and dos Santos (2018) used this theory to carry out an explanatory investigation on which factors induce the intention of contribution by solvers in crowdsourcing initiatives.

Critique of: *Social exchange theory:* Blau (1964) believed that human behaviour is motivated by the expected rewards of their behaviours, and these rewards are usually given by others. The central idea of social exchange theory is the exchange of social and material resources is the basic form of human interaction. The theory explains human behaviour in social exchange from the perspective of cost-benefit. Cost refers to the penalty or reward that people face in their interactions with others, including direct costs (resources given to others in exchange for something else), investment loss (using the time and benefits that may be rewarded for others for personal skill development) and opportunity cost (missing opportunities to obtain rewards from other interactions). Benefit refers to the resources that are positively strengthened, including happiness, fulfilment and satisfaction (the continuum from concrete to symbolic), including personal attractiveness, social appreciation, social identity, attention/prestige, power, etc. Social exchange theory has been used to understand the phenomenon of knowledge sharing in online communities and organisations (Hsu *et al.*, 2007; Ye, Feng and Choi, 2015).

Selection process: Of the theories mentioned, social exchange theory/approach seems on the outset as being the most logical and appropriate for this chapter is as the main theoretical framework in finding solvers' motivation factors of SMEs CCI:

Additional Rationale:

Source: Elsevier is a highly respected publisher of quality research. The works of Ye and Kankanhalli (2017) declared in the Journal of Strategic Information Systems has an Impact Factor of 5.231 and Citescore of 10.1.

Breadth: Both 'positive' and 'negative' motivation factors should be considered. Compared with the tasks launched by large and famous companies, solvers in SMEs CCI are more likely to face risks, such as intellectual proper right (IPR) risk which is mainly caused by SMEs' lack of IPR protection ability and the company's moral risk. Under this circumstance, solvers tend to not only consider about what they will gain, but also the effort/cost they have to put. Back to the other theories analysed above, few researchers take both the beneficial (i.e. intrinsic and extrinsic) factors and the cost and/or risk factors into consideration.

Appropriateness: Social exchange theory can better cater to the characteristics of crowdsourcing contest innovation with the nature of online community. Compared with other types of crowdsourcing, crowdsourcing contest has more uncertainties inherently (Wang and Wang, 2019). This feature brings challenges to the predictive power of expectation-confirmation theory:

- Expectation-confirmation theory conceptualises the perceived usefulness of technical product to indicate people's expectation, however, in crowdsourcing contest, solvers care/expect to obtain utilitarian or hedonic value (Sun, Fang and Lim, 2012).

- Expectation-confirmation theory holds that what to expect from an interaction is the product material attributes or quality. However, in crowdsourcing contest tasks, especially the ones submitted by SMEs, solvers' participating purpose is definitely not only on monetary reward, but also social/psychological achievement.

Rigour: Social exchange theory can also be used to explain solvers' intention of continuous participation. Continuous participation of solvers is crucial to the sustainability and success of crowdsourcing while social exchange assumes that there is a relatively long-term relationship of interest, rather than a one-time exchange. Although, expectancy theory is widely used to explain solvers' continuance participation, it is not suitable to be utilised to do study in the initial stage of crowdsourcing innovation.

However, there are challenges remaining in the utilisation of social exchange theory (Cropanzano *et al.*, 2017):

- Overlapping constructs that need to be more clearly distinguished
- Insufficient appreciation to the positive or negative hedonic value of these various constructs
- An assumption of bipolarity, which treats negative constructs (e.g. abuse) as the absence of positive constructs (e.g. support)
- Theoretically imprecise behavioural predictions

Hence, while social exchange theory provides the overarching logic for the conceptual model of this chapter, other relevant literature is also utilised for more specific theorising of the constructs in the research context and more reasonable research assumption and conceptual model.

2.3 Research Assumptions and Conceptual Model

According to social exchange theory, people seriously weigh the rewards and costs from their social interaction. Only when the reward for participating in an event is higher than the cost, will people have the motivation to participate in the event. Therefore, the solvers' willingness to participate in SMEs CCI is affected by their perceived benefits and costs.

Benefit perception

Benefits brought by participating in CCI are well documented by studies.
Material rewards, psychological comforting, new knowledge and skills gaining

are the most typical benefits that solvers can get from crowdsourcing contest tasks. Meanwhile, in this research, it is believed that the impact of social belonging on solvers' participation motives cannot be ignored. According to Baruch, May and Yu (2016), retirement, disability or long-term health problems are major drivers for participation. Although retirement, disability or health problems can prevent individuals from engaging in traditional work and integrating into society, crowdsourcing gives them an equal opportunity in life. Compared with large enterprises, the SMEs CCI tasks are less difficult and have a short time span, that is, the threshold is low. This group of people can participate in the solution of this kind of innovative tasks. Regardless of age and physical condition, as long as there is wisdom and knowledge that can be exchanged, then they are contributors and are needed by society. In summary, the benefit perception is divided into four dimensions: material, knowledge acquisition and sharing, reputation and social belonging. The material factors are external motives, and knowledge acquisition and sharing, reputation and social belonging are all non-material factors, which are internal motives.

<u>Cost perception</u>

Early research has shown that crowdsourcing should be adopted and applied due to its benefits (Ågerfalk and Fitzgerald, 2008). However, considering the risks in crowdsourcing contest, it is necessary to analyse the barriers of the participation in SMEs CCI. These barriers originate from communicational, organisational or legal incidents or risk factors (Lüttgens *et al.*, 2014). Referring to studies of Sun *et al.* (2015), Qin *et al.* (2016) and Malhotra *et al.* (2017), combining with the features of SMEs, the barriers of solvers to participate in SMEs CCI are summarised as follows: (1) Seekers' opportunistic behaviour: seekers might refuse to pay after receiving the solutions by giving unfavourable reviews to all the solutions which result in the loss of time and energy of solvers; (2) Trust and confidentiality issues in the open and digital environment: for SMEs, due to their inability to build their own platforms, they can only rely on third-party crowdsourcing platforms, which means that SMEs cannot effectively control the CCI process and results. Coupled with the lack in integrity management and results management mechanisms and results screening capabilities, it is difficult for SMEs to protect intellectual property rights, which will reduce the trust of solvers in their issued CCI tasks; (3) The relatively low monetary rewards provided by SMEs CCI tasks: this leads to a problem that when solvers find that the task is difficult, but the reward amount and the expected reward amount are quite different, they will choose another task. Therefore, considering the above obstacles, this thesis divides the cost perception into three dimensions: task complexity, intellectual property risk, and waste of resource.

Meanwhile, as mentioned before, continuous participation of solvers is key to the long-term result of crowdsourcing innovation, the influencing factors of continued participation in SMEs CCI need to be studied as well (Sørebø and Eikebrokk, 2008). Based on the above ideas, solvers' willingness to participate in SMEs CCI is proposed from two aspects: perceived benefit and perceived cost and try to build up a theoretical model of solvers' continuous participating behaviour.

2.3.1 Research Hypotheses

(1) Perceived benefit hypotheses

Material factors

Material factors refer to rewards for cash, materials, and platform privileges obtained by solvers for participating in SMEs CCI. Material reward is often the most direct and effective factor in social behaviour. Studies have found that material rewards such as money are often the most direct and important motivational factors that stimulate people's social behaviour in crowdsourcing contest (Brabham, 2008; Zheng, Li and Hou, 2011). According to social exchange theory, the expectation of monetary returns can motivate individuals to choose actions (Molm, 1997). Therefore, the following hypothesis is proposed:

H1: Material factors are positively correlated with the perceived interest of solvers' participation in SMEs crowdsourcing contest innovation.

Knowledge sharing

The desire for knowledge is an instinctive desire born in life. Knowledge is the base for people's practical skills to improve, and it also provides reliable information for people's interaction with their surroundings. Many crowdsourcing communities are built for the purpose of knowledge creation and interaction (such as the Xiaomi BBS[6]). Although crowdsourcing platforms such as Zbj.com and 680.com mainly conduct reward contest mode (i.e. pitch mode), a functional platform for knowledge exchange and discussion has also been opened in the past two years. Besides, an important feature of the innovation process of SMEs is to maintain some informal communication and interoperability with customers and to be flexible enough in knowledge creation (Rahman and Ramos, 2010; Cheng and Shiu, 2018). Therefore, the following hypothesis is proposed:

> **H2:** Knowledge acquisition and sharing are positively correlated with the perception of interest of solvers' participation in SMEs CCI.

Reputation

Material factors can only meet individuals' short-term needs, and the increasing attention to the implicit element of reputation reflects the characteristics of their pursuit of long-term interests. Reputation refers to the complex integration of the people's remarkable personal characteristics and accomplishments, outstanding behaviours, and established images in the past period (Siddiki *et al.*, 2017). Out of consideration for strengthening or maintaining reputation, solvers have an inherent motivation to increase the investment in knowledge and the input of their efforts. On the one hand, crowdsourcing acquires and transmits the wisdom of the public, and solvers can realise the opportunity to participate in big enterprise's projects through crowdsourcing (Maiolini and Naggi, 2011); on the other hand, due to the constraints of innovation resources, SMEs tend to adopt the method of task decomposition and reintegration, and the knowledge correlation between crowdsourcing projects is strong, which determines its

[6] http://www.miui.com/bbs/

reputation effect is particularly obvious. For example, Citroen used the crowdsourcing method for component integration to design the appearance of some new car models including shell colour and interior decoration, which gave solvers more creative space and significantly improves their enthusiasm (Wang, Suo and Chen, 2017). Therefore, the following hypothesis is proposed:

H3: Reputation is positively correlated with the perception of interest of solvers' participation in SMEs CCI.

Social belonging

Social motivation usually stems from the willingness of individuals to meet the needs of social belonging and their emphasis on the value of group membership (Ashforth and Mael, 1989). Without doubt, one of the main goals of crowdsourcing contest is to provide valuable solutions to innovation problems, usually only individuals with a high sense of organisational belonging and identity may be willing to actively contribute to the realisation of this goal (Acar, 2019). Furthermore, it is believed that the SMEs CCI tasks will attract more solvers to join because of the low barriers to participation, which can give each solver a greater sense of social belonging. Therefore, the following hypothesis is proposed:

H4: Social belonging is positively correlated with the perception of interests of solvers' participation in SMEs CCI.

(2) Perceived cost hypotheses

Task complexity

Task complexity is an important factor which can be measured in terms of the dimensions of analysability and uncertainty (Wood, 1986; Liu and Li, 2012). To be specify, in this research, task is regarded as any project released by SMEs on crowdsourcing contest innovation. It is believed that the higher the task complexity, the higher the cognitive requirements, effort and attention level (collectively referred to as information processing ability) of the problem solver.

Under the “cost” effect caused by this overload situation, individuals will lose interest in performing tasks.

Crowdsourcing innovation has obvious knowledge-intensive characteristics, which is essentially an activity to absorb the wisdom of the public. The complexity of the crowdsourcing innovation task puts forward higher requirements on the knowledge domain and the scope and quantity of the information sources, which increases the cost of execution (Borromeo, Laurent and Toyama, 2016). So, if the task complexity and the participation threshold are too high, the cost of labour, financial resources and energy will definitely be higher than the material benefits, pleasure, pride and satisfaction obtained from the task, the solvers’ enthusiasm for participation will be significantly reduced. Therefore, the following hypothesis is proposed:

H5: The task complexity is positively related to the cost perception of solvers’ participation in SMEs CCI.

Intellectual property risk

Crowdsourcing innovation is a demonstration of the achievements of the public’s intellectual innovations, which belongs to the product of knowledge and intelligence. Not like physical goods, intellectual products are easy to transmit through the network, and the cost of copying them is low, intellectual property protection is difficult, and the attribution of innovation achievements is controversial. By sharing a part of unique knowledge, knowledge contributors will lose the sole right to claim the benefits brought about by this knowledge (Davenport and Prusak, 1998), and this risk cost will harm the benefits brought by sharing knowledge.

Furthermore, the crowdsourcing platform generally requires solvers to explain the details of the submitted solution for its quality evaluation. In this scenario, the seeker may generate opportunistic behaviour , that is, taking the solution as its own and refusing to pay for the solution, Especially for SMEs who are known for their weak awareness of intellectual property rights, prominent credibility problems and high risk of results abuse (Qiao, 2017). On the other hand, SMEs seekers are also concerned that solvers will submit non-original plans or do not own the intellectual property rights to submit solutions, increasing the risk of third-party infringement (de Beer *et al.*, 2017). Therefore, the following hypothesis is proposed:

> **H6:** Intellectual property risk is positively related to the cost perception of solvers' participation in SMEs CCI.

Waste of resources

Most of the current SMEs crowdsourcing innovations adopt the award contest model with the main feature of "winner-takes-all". Despite a lot of effort, only one solution will be selected in this model. Especially, sometimes the solvers cannot complete the task, or forget the deadline for submitting the task for some special reasons, which leads to a lot of wasted time and energy costs (Van Alstyne, Fiore and Schneider, 2017). In the field of crowdsourcing, "resource" refers to the effort to solve problems on a crowdsourcing platform to bridge the gap between solvers' existing knowledge and the current knowledge needed to solve the problem. Obviously, in the CCI, the likelihood of solvers to achieve the predicted results is inversely correlated with the number of solvers. Since the participation threshold is low and the number of solvers is generally higher than that of large enterprises, this theoretically will further reduce the probability of winning for each solver in the SMEs CCI and increase the cost of wasting resources. Therefore, the following hypothesis is proposed:

> **H7:** The waste of resources is positively correlated with the cost perception of solvers' participation in the SMEs CCI.

(3) Hypotheses of perceived benefits, perceived costs and participating willingness

According to the social exchange theory, when considering a decision or taking an action, people tend to compare the perceived benefits from the action with the perceived costs, so as to measure the total utility brought by the action. Only when the perceived benefits are higher than the perceived costs, people have the will to take the action. Therefore, the following hypotheses are proposed:

H8: Perceived benefit is positively related to the willingness of solvers' participation in the SMEs CCI.

H9: Perceived cost is inversely related to the willingness of solvers' participation in the SMEs CCI.

(4) Participation willingness and behaviour hypothesis

Willingness is the subjective possibility that the subject makes a certain decision or takes a certain action. As a leading variable, willingness plays an important role in predicting the generation of behaviour (Pouta and Rekola, 2001). In addition, according to the theory of social planning, individual behavioural willingness will exert a strong guiding effect on their behaviours. Therefore, the following hypothesis is proposed:

H10: The willingness of solvers' participation in the SMEs CCI is positively correlated with their continuous participation behaviour.

(5) Solvers' continuous participation behaviour hypothesis

According to the PAM-ISC (post-acceptance model of IS continuance) model (Bhattacherjee, 2001; Zhong, Wang and Qiu, 2011), after the initial willingness to participate in an action, solvers will form certain expectations, and in the follow-up action, they will confirm whether the expectations have been met according to their own experience. For crowdsourcing solvers, the experience involved generally includes platform usability perception, usefulness perception, network platform belonging. Among them, the platform usability perception refers to the solvers' objective evaluation of the operation simplicity and ease of use of the information system (Leimeister *et al.*, 2009), and is the most intuitive experience perception of information system users. SMEs CCI relies mainly on third-party crowdsourcing platforms whose interface is clear and easy to operate and is equipped with detailed function navigation and operation instructions. Solvers can easily master the use of the platform. Therefore, the following hypothesis is proposed:

H11: The platform usability perception is positively correlated with the solvers' participating behaviour in SMEs CCI.

2.3.2 The Conceptual Model of Motivation Factors of Solvers' Participation in SMEs Crowdsourcing Contest Innovation

According to the theoretical hypotheses, the conceptual model of solvers' participating motivation in SMEs CCI is built up and shown in Figure 2- 1. Solves' participation willingness is positively affected by the benefit perception which is consisted of the constructs including material, knowledge acquisition and sharing (KAS), reputation and social belonging, while negatively affected by the cost perception which is consisted of the constructs including task complexity, intellectual property (IP) risk and waste of resource. Meanwhile, combining with the participation willingness which can be regarded as the initial involvement, the factor of platform usability is chosen to explore the continuous participation behaviour in SMEs CCI.

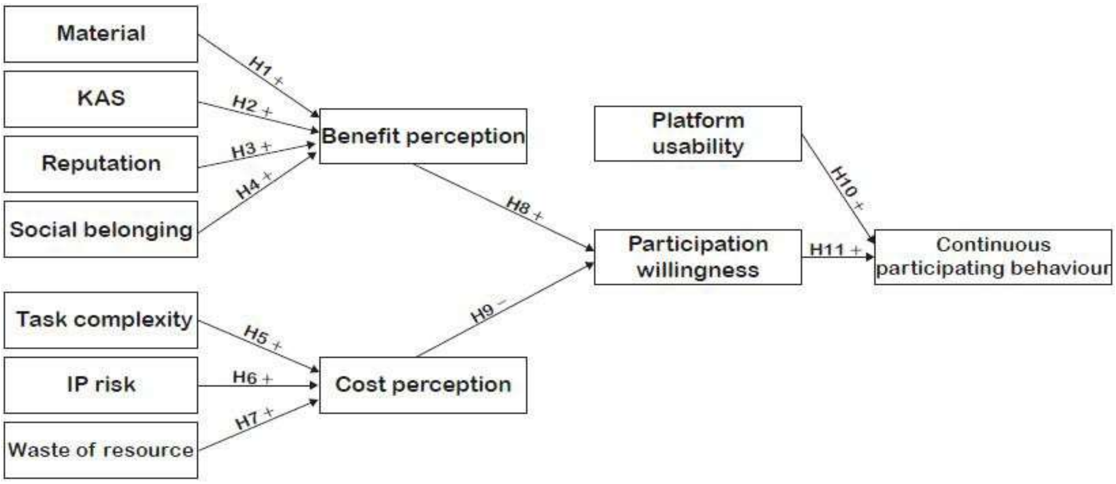

Figure 2- 1 Conceptual model of motivation factors of solvers' participation in SMEs CCI

(designed by the author)

2.4 Empirical Research

2.4.1 Questionnaire Design

The questionnaire is designed based on the existing literature and self-development by the author. The first nine items (Part 1) in the questionnaire (V1-V9) are the Internet users' basic information. The motivation factors (from benefit perception and cost perception), willingness of solvers' participation, platform usability and solvers' continuous participation behaviour proposed in Section 2.2 are divided into 12 latent variables. Each latent variable is described by 2-3 indicator variables, and there are totally 27 indicator variables (V10-V36, Part 2 of the questionnaire). The five-point Likert scales in which 1 = "strongly disagree" and 5 = "strongly agree" are adopted for each indicator variable. Some indicator variables (i.e. measurement items) of the latent variables of the questionnaire are learnt from the content-related research, and some are not only based on the existing research, but also developed considering the features of SMEs CCI by the author (Table 2- 3). For example, the items of 'material' are extracted from the research of (Xia and Zhao, 2017), and the items of 'knowledge acquisition and sharing' are based on the study of Reeve, Deci and Ryan (2004) and self-development. The design of self-developed variables (such as V13) is based on expert discussion and pre-investigation:

Firstly, the structure and the chosen of variables were determined by the author first.

Secondly, in order to ensure the generality of the questionnaire (the question setting has universal meaning), rationality (the questionnaire is closely related to the research subject), and the logic (the questionnaire is systematic), repeated discussions were conducted with the author's supervisors so as to set up the prototype of the questionnaire.

Thirdly, the questionnaire was distributed to master students and research students of the Centre of Centre for Competitive Creative

Design, Cranfield University as a pre-survey, and based on the result, the questionnaire was refined in order to improve its validity.

Table 2- 3 Composition of measurement items of the questionnaire

Latent variable	Indicator variable	Reference
Material (MT)	V10 Participating in the SMEs CCI provides the opportunity to earn additional bonuses V11 Participation in the SMEs CCI provides more part-time job opportunities	Xia and Zhao (2017)
Knowledge acquisition and sharing (KAS)	V12 Participation in the SMEs CCI can gain knowledge and technology, which improves problem solving ability V13 On the CCI platform, you can share technical knowledge with everyone and promote progress together, which gives you a very sense of accomplishment	Reeve, Deci and Ryan (2004), self-developed
Reputation (RT)	V14 If your solution is selected, your reputation and popularity on the platform will be greatly improved V15 If your solution is selected, you can get points and level upgraded, the chance of winning the next project will be improved V16 Participating in the SMEs CCI can promote your future career development	Huang and Cao (2018), self-developed
Social belonging (SB)	V17 Participating in the SMEs CCI can make friends and improve the sense of social belonging V18 Social identity and other emotional factors will promote your participation in the SMEs CCI	Acar (2019)
Task complexity (TC)	V19 The SMEs CCI is relatively difficult and may not be completed by a single person. This will limit your motivation to participate V20 The description of the SMEs CCI is not clear enough, which may affect your understanding of the task, thereby limiting your enthusiasm for participation	Qiao (2017), self-developed

Intellectual property risk (IPR)	V21 You are very worried that the submitted solution will be stolen and imitated by SMEs (or others), which affects your willingness to participate V22 You are very worried that SMEs will cheat during the program selection process, which affects your willingness to participate V23 If the clause of the SMEs CCI does not clearly stipulate the ownership of the intellectual property rights of the solution, your willingness to participate will be seriously affected	Lakhani and Panetta (2007), self-developed
Waste of resource (WOR)	V24 The SMEs CCI is a competitive innovation mode. Once your solution fails to win the bid, all your efforts will be in vain. This will affect your enthusiasm for participation V25 Sometimes, you will fail to submit the solution for some special reasons or forget the deadline, which will result in wasted effort. This will affect your enthusiasm for participation	Van Alstyne, Fiore and Schneider (2017), self-developed
Benefit perception (BP)	V26 Participating in the SMEs CCI is generally very beneficial for developing your creativity V27 Participating in in the SMEs CCI is generally very beneficial to your work and study	Zhong, Wang and Qiu (2011)
Cost perception (CP)	V28 You think participating in the SMEs CCI will cost you a lot, but it is difficult to get the corresponding return V29 There are many uncertain factors in the SMEs CCI, which may cause the final task to be unsolved. This makes you feel a great sense of loss	Huang and Cao (2018), Dong and Yang (2008)
Participation willingness (PW)	V30 You are willing to frequently participate in the SMEs CCI V31 You are happy to log into Zbj.com, InnoCentive and other crowdsourcing platforms frequently, and continue to pay attention to CCI projects released by SMEs	Pouta and Rekola (2001)
Platform usability (PU)	V32 The SMEs CCI platform you chose is very convenient to use	Taylor and Todd (1995), Zhang (2019)

	V33 You can master the rules of crowdsourcing platforms V34 Through the crowdsourcing platform, you can easily participate in the SMEs CCI	
Continuous participating behaviour (CPB)	V35 You will continue to actively participate in the SMEs CCI in your spare time in the future V36 You will continue to find interesting task items on crowdsourcing platforms in the future	Chen, Chen and Kinshuk (2009)

2.4.2 Data Collection

This chapter uses convenience sampling to collect sample data because of its low costs and difficulties compared with probability sampling (Kumar, Talib and Ramayah, 2014). Respondents (solvers) were approached from Zbj.com - China's largest commercial service crowdsourcing platform, with more than 13 million members providing creative services, such as graphic design, animation video, decoration design, copywriting, industrial design, engineering design, marketing and other fields.

Questionnaires were distributed in the following ways:

- Community post: Distributing directly onto the Zbj.com platform as a crowdsourcing opportunity. The questionnaire was distributed as a piece counting task, once the questionnaire is answered, the solver can get the fixed reward. There are 8% of total responses are obtained through this way.

- Targeted email response: As Zbj.com has an open talent pool of solvers which offers a direct access to the contact information (such as QQ number[7] and email address) of them, questionnaires were sent to solvers via emails. However, due to the lack of motivation, the respondents' willingness to answer the questionnaire is low. In addition, there are many invalid email addresses, so there is no useful data collected by this way.

[7] https://ssl.zc.qq.com/v3/index-en.html

● Third party network: Through Wjx.cn[8] and Wechat Moment[9], questionnaires are sent to the author’s friends and colleagues who have the intention to participate in or have relevant experience in crowdsourcing innovation. This distribution method works the best. Wjx.cn is the most professional online questionnaire survey and evaluation platform in China, focusing on providing users with powerful and humanised online questionnaire design and data collection functions. Compared with traditional survey methods, Wjx.cn has obvious advantages of fast, easy to use and low cost. 92% of the data are collected through this way.

The questionnaire survey data was obtained from the beginning of June to the end of July 2019. During the questionnaire collection period, a total of 256 questionnaires were received, of which 39 invalid questionnaires were excluded, finally, a total of 217 valid questionnaires were received.

2.4.3 Descriptive Statistics of the Respondents

The basic characteristics of the respondents and the mean and standard deviation of each variable - capturing gender, age, educational background, monthly income, the number of times accomplished SMEs CCI tasks, participation frequency and types of the seeker. Inspired by the way of data display of Zhai *et al.* (2018) and Sardo and Serrasqueiro (2017), results are shown in Table 2-4.

[8] https://www.wjx.cn/
[9] https://help.wechat.com/cgi-bin/micromsg-bin/oshelpcenter?opcode=2&plat=android&lang=en&id=120813euEJVf141023RBfMjm

Table 2- 4 Basic characteristics information

Characteristics	Item	Frequency	Percent
Gender	male	105	48.39%
	female	112	51.61%
Age	< 20	10	4.61%
	20-29	143	65.90%
	30-39	48	22.12%
	40-49	9	4.15%
	>50	7	3.23%
Highest qualification	high school degree or under	6	2.76%
	higher education degree	32	14.75%
	bachelor’s degree	111	51.15%
	master’s degree	50	23.04%
	doctor’s degree	18	8.29%
Monthly income	<RMB 3000	46	21.20%
	RMB 3000-4999	49	22.58%
	RMB 5000-9999	81	37.33%
	RMB 10000-19999	35	16.13%
	>RMB 19999	6	2.76%
Number of participations in SMEs CCI	never	40	18.43%
	1-5 times	92	42.40%
	6-10 times	59	27.19%
	11-20 times	22	10.14%
	> 20times	4	1.84%

It can be seen from Table 2- 4 that 81.6% of the 217 respondents surveyed have participated in crowdsourcing contest at least once, and more than 88% of the tasks they solved are submitted by individuals or SMEs, which indicates that the characteristics of the questionnaires are in line with this research theme - “participating motivation in SMEs CCI”. From the perspective of demographic characteristics, the proportion of female respondents is 51.6% and the proportion of respondents with the bachelor degree, graduate degree and above has reached 82.5%. The most concentrated age group is 20-29 years old, accounting for 65.9%. Why do career starters fancy SMEs CCI? It is mainly because of the task attributes. SMEs CCI tasks offer a new form of employment which refers to the realisation of flexible and platform-based employment form that is different from the formal stable traditional employment. Young people’s faster ability to adapt to the Internet economy era and their higher acceptance of new employment forms make them become the main labour force of crowdsourcing contest innovation. And the proportion of those with a monthly income of more than 5,000 yuan is 56.2%. The above information indicates that solvers of SMEs CCI are basically young intellectuals with higher education and upper middle income, and it is consistent with the characteristics of active solvers on Zbj.com, and also coincides with the intellectual and technical requirements of a crowdsourcing contest platform. In addition, in terms of the number of participations, near half of the surveyed respondents only participated 1-5 SMEs CCI tasks. The descriptive statistics of each indicator variable are shown in Table 2- 5.

Table 2- 5 Statistics of the mean value and variance of each indicator variable

Latent variable	Indicator Variable	Mean	Variance
MT	v10	3.76	.621
	v11	3.78	.643
KAS	v12	3.81	.617
	v13	3.83	.633
RT	v14	3.81	.672
	v15	3.80	.669
	v16	3.86	.601
SB	v17	3.67	.767
	v18	3.60	.732
TC	v19	3.31	.826
	v20	3.34	.883
IPR	v21	3.23	.926
	v22	3.25	.940
	v23	3.50	.918
WOR	v24	3.16	.911
	v25	3.13	1.005
BP	v26	3.82	.602
	v27	3.84	.516
CP	v28	2.92	.739
	v29	2.99	.810
PW	v30	3.70	.574
	v31	3.56	.636
PU	v32	3.52	.695
	v33	3.39	.822
	v34	3.47	.796
CPB	v35	3.59	.650
	v36	3.61	.610

As mentioned earlier, this thesis divides the factors that affect solvers' willingness to participate in SMEs CCI into two categories: benefit perception and cost perception. Benefit perception is determined by the four latent variables of material motivation, knowledge sharing, reputation, and social attribution, while cost perception is explained by three latent variables of task complexity, intellectual property, and waste of resources. The mean value of the benefit perception variables is basically above 3.65 and the average mean value of the cost perception variables is mostly around 3.3, especially, the mean value of the latent variable – cost perception is below 3. In addition, the variance of benefit perception variables is significantly lower than that of cost perception variables. This indicates that the respondents agree that they can get positive benefits from SMEs CCI, and their perception of cost is not obvious.

2.4.4 Reliability and Validity Analysis

According to the theoretical hypotheses in Section 3.4.1, the reliability and validity analysis (Price *et al*., 2020) of 12 latent variables including material reward, knowledge sharing, reputation, social attribution, task complexity, intellectual property, waste of resources, benefit perception, cost perception, participation intention, platform ease of use perception and continuous participating behaviour are carried out. The reliability test uses the Cronbach's α value[10] and the composite reliability (CR)[11] value; the method of discriminating convergence validity uses the average variance extracted (AVE)[12] value and the latent variable covariance matrix. SPSS.22 is used to output the Cronbach's α value of latent variables, by getting each indicator variable's loading factor, the CR and AVE value of all the latent variables are calculated in excel, and Mplus7 is adopted to get the covariance matrix of latent variables. Results are shown in Table 2-6 and Table 2-7.

[10] https://stats.idre.ucla.edu/spss/faq/what-does-cronbachs-alpha-mean/
[11] https://www.statisticshowto.com/composite-reliability-definition/
[12] https://www.igi-global.com/dictionary/average-variance-extracted/45252

Table 2- 6 Cronbach's α, CR, AVE of each latent variable

Latent variable	Cronbach's α	CR	AVE
MT	0.593	0.831	0.711
KSA	0.811	0.914	0.841
RT	0.805	0.885	0.720
SB	0.727	0.880	0.786
TC	0.760	0.893	0.807
IPR	0.871	0.921	0.795
WOR	0.770	0.897	0.813
BP	0.836	0.925	0.860
CP	0.703	0.871	0.772
PW	0.805	0.912	0.838
PU	0.849	0.909	0.768
CPB	0.867	0.938	0.883

Table 2- 7 Covariance matrix

	MT	KSA	RT	SB	TC	IPR	WOR	BP	CP	PW	PU	CPB
MT	.449											
KSA	.257	.525										
RT	.265	.328	.466									
SB	.199	.220	.271	.589								
TC	.084	.076	.148	.119	.689							
IPR	.063	.027	.033	.129	.219	.737						
WOR	.067	.034	.022	.048	.274	.419	.779					
BP	.260	.352	.369	.269	.089	.020	.005	.480				
CP	-.036	-.082	-.067	.025	.240	.399	.434	-.077	.597			
PW	.166	.277	.289	.231	.030	-.028	-.023	.321	-.134	.506		
PU	.207	.183	.234	.221	.074	.034	.035	.224	-.095	.282	.592	
CPB	.185	.203	.230	.216	.103	.018	.011	.217	-.091	.282	.397	.556

It can be seen from Table 2- 6 that except for material motivation, the Cronbach's α coefficients of all latent variables are above 0.7, indicating that the questionnaire basically meets the internal consistency requirements. In particular, the CR values of knowledge sharing and acquisition (KSA) and reputation (RT) both exceed 0.8, indicating that the above two variables' scales designed in this chapter are reasonable and credible. In addition, the AVE value of all latent variables in Table 2- 6 reaches more than 0.5, and the covariance of each latent variable with itself in Table 2- 7 is greater than the absolute value of all covariances with other latent variables. All these indicate that the questionnaire has high convergence validity.

2.4.5 Hypothesis Testing

According to the proposed hypothesis, a structural equation model for the motivation of solvers' participation in SMEs CCI is constructed. With the help of Mplus7, the model fit and the proposed hypotheses are tested. The model coefficient results are shown in Table 2- 9. It can be seen from this table that a total of 9 hypotheses are supported, of which one is significant at the 5% level, and the other 8 are significant at the 1% level. Two other assumptions are not supported.

Table 2- 8 Model fit indices

Index	Recommended value	Model value	Acceptance
RMSEA	<0.05 good fit, <0.10 reasonable fit	0.063	Reasonable
CFI	Above 0.9	0.925	Good
TLI	Above 0.9	0.907	Good
SRMR	<0.05 good fit, <0.10 reasonable fit	0.062	Reasonable
$\frac{x^2}{df}$	<3 good fit, <5 reasonable fit	533.4/285=1.872	Good

Table 2- 9 Parameter estimation and hypothesis testing of analytical models

Path	Estimate	Standard error	critical ratio	*p* value	Hypothesis	Support
BP↙ MT	0.205	0.092	2.227	0.026 **	H1	Positive
BP↙ KSA	0.256	0.094	2.721	0.007 ***	H2	Positive
BP↙ RT	0.504	0.117	4.316	0.000***	H3	Positive
BP↙ SB	0.098	0.068	1.440	0.150	H4	Negative
CP↙ TC	0.072	0.077	0.932	0.351	H5	Negative
CP↙ IPRR	0.309	0.098	3.145	0.002***	H6	Positive
CP↙ WOR	0.621	0.113	5.494	0.000***	H7	Positive
PW↙ BP	0.764	0.043	17.715	0.000***	H8	Positive
PW↙ CP	-0.173	0.063	-2.751	0.006***	H9	Positive
CPB↙PW	0.226	0.069	3.278	0.001***	H10	Positive
CPB↙PU	0.709	0.055	12.796	0.000***	H11	Positive

Note: **95% confidence interval excludes the null value; ***99% confidence interval excludes the null value.

It can also see from Table 2- 9 that the path coefficients of the three factors: material, knowledge acquisition and sharing, and reputation are 0.205, 0.256, and 0.504 respectively, and the critical ratio values are 2.227, 2.721, and 4.316 respectively. The material motivation is significant at the 5% level, and the two non-material motivations for knowledge acquisition and sharing and reputation are significant at the 1% level. Hence, hypotheses H1, H2, and H3 are supported, and the significance level of non-material motivation is higher than that of material motivation. The path coefficient of social attribution factor is 0.098, the critical ratio value is 1.440, the *p* value is 0.150>0.05, indicating that social attribution is not significantly related to interest perception, and H4 does not receive the empirical support. Similarly, H6, H7 and H8 are supported.

Interestingly, the path coefficient of task complexity is only 0.072, and the critical ratio value is only 0.932, which is not significant at the 5% level, indicating that task complexity is not significantly related to cost perception, and H5 is not supported. From the analysis results of cost perception on participation motivation, the path coefficient is -0.173, the critical ratio value is -2.751, and the path coefficient is also significant at the level of 1%, indicating that cost perception significantly affects the solvers' willingness to participate in SMEs CCI, and H9 is supported. Finally, H10 and H11 are supported through the analysis of the critical ratio value and the significant level.

In addition, from the overall fit index of the model (Table 2- 8), the RMSEA (Root Mean Square Error of Approximation), CFI, TLI, and SRMR (Standardized Root Mean Square Residual) index values are all within the optimal range, indicating that the model meets the fit requirements well.

2.5 Path Analysis and Key Findings

With the help of Mplus7, the relationship between all potential variables and observed variables is found out, and the OLS (ordinary least squares) is utilised as the coefficient estimation method to conduct regression analysis on motivation factors from benefit perception and cost perception, participation willingness and continuous participation behaviour respectively, the path diagram of the structural equation model is obtained, which is shown in Figure 2- 2. It can be seen that all latent variables have significant path coefficients for their subkeys at the level of 1%, which again shows that the scale of the questionnaire has high reliability and validity. Although not all of the factors affecting benefit perception and cost perception pass the hypothesis test, the behaviour path of continuous participation in SMEs CCI (i.e. benefit perception, cost perception → willingness to participate, ease of use of platform → continuous participation behaviour) is empirically supported.

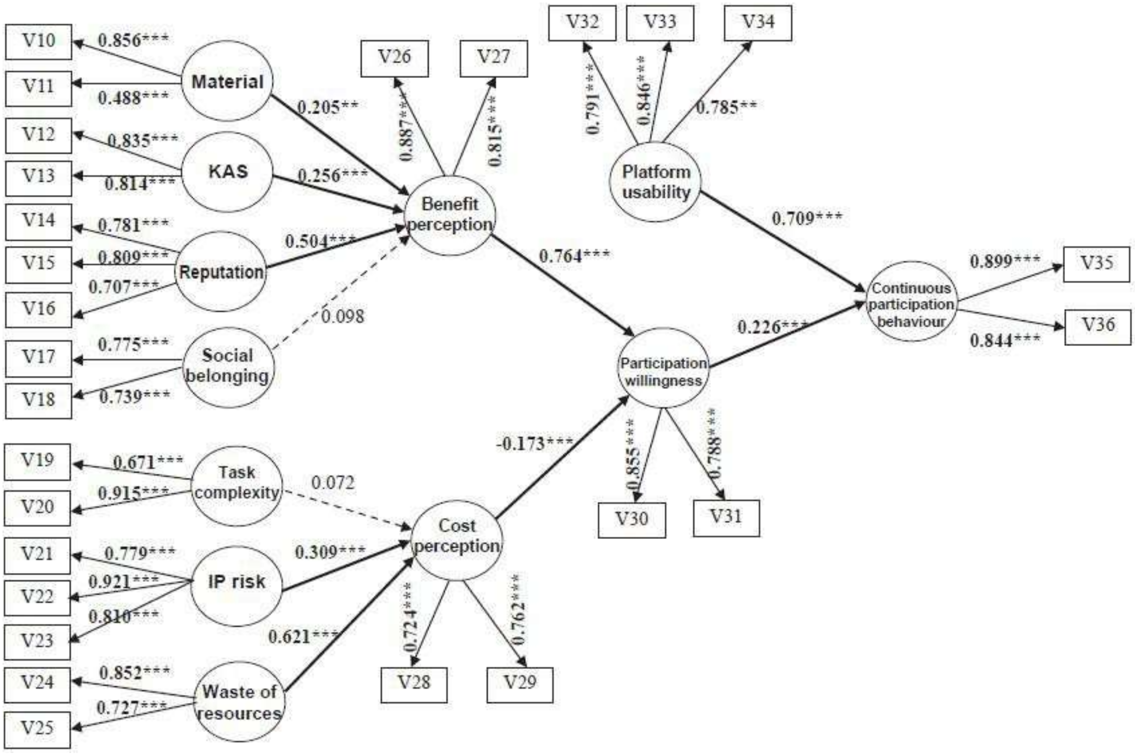

Figure 2-2 Path diagram of the structural equation model of solvers' participation willingness in SMEs CCI

Note: **95% confidence interval excludes the null value; ***99% confidence interval excludes the null value.

<u>Here are the key research findings:</u>

Finding (1): Material motivation is an important factor that affects the perceived benefits of solvers' participation in SMEs CCI, but it is not the most important factor. This is because, on the one hand, the solvers can clearly expect that the bonus of SMEs CCI will not be very high compared with large companies; on the other hand, this finding is also consistent with the view of Boudreau and Lakhani (2013) which is "crowds are energised by intrinsic motivations—such as the desire to learn—that are more likely to come into play when people decide for themselves what problems to attack."

Finding (2): The path coefficient and significance of the two non-material factors which are knowledge acquisition and sharing and reputation are higher than the material motivation. To a large extent, most solvers in SMEs CCI hope to improve the way and efficiency of knowledge acquisition and improve their problem-solving skills through the platform sharing community, and they can also share their knowledge with other solvers to promote common progress and get full pleasure and pride from them. On the other hand, some SMEs seekers will often enter the knowledge exchange platform and participate in the discussion of innovative technology topics with solvers. This also increases the solvers' confidence in SMEs CCI and strengthens their willingness to participate. In terms of reputation, another purpose of solvers to participate in SMEs CCI is to use the platform's high popularity to expand their popularity. If they win, solvers can not only improve their ability level under the existing point reward mechanism and improve their chances of winning in the next crowdsourcing task, but also the individual ability information will spread through the crowdsourcing platform, indirectly helping them to obtain high-quality employment choices and improve their long-term interests to some extent. Therefore, the role of non-material motivation such as knowledge sharing, acquisition, and reputation is more obvious, and it is necessary to build an incentive mechanism that combines material and non-material factors. In addition, from the results of the empirical study, social belonging does not significantly increase the benefit perception of solvers, it is believed to be possible because solvers feel that the sense of security and belonging obtained from the online platform is always weaker than the real sense of social belonging.

Finding (3): The complexity of crowdsourcing tasks does not necessarily increase solvers' cost perception in SMEs CCI. According to the results of empirical research, 65% of solvers believe that the difficulty of crowdsourcing tasks from SMEs is generally lower than that of large enterprises, and the increase in complexity is often accompanied by the increase of bounty bonuses, which will basically not weaken their participating willingness. Furthermore, some solvers believe that challenging tasks can stimulate their desire to conquer, and they may gain greater pride. The main reason for solvers to perceive the cost of participation is the risk of intellectual property rights and the waste of resources. Young solvers generally have a strong sense of intellectual property rights. They worry that SMEs, unlike large enterprises, do not have a complete set of mechanisms to protect property rights, have a weak sense of property rights, and tend to steal good results in the process of program evaluation. In addition, 50% of solvers are also worried that the works submitted on the crowdsourcing platform are imitated or misappropriated by other solvers, which seriously affects their willingness to participate. Another important cost perception factor is the risk of resource waste. Due to the implementation of the "winner-takes-all" complete contest mode on Zbj.com, material resources are blindly invested without knowing the information of other competitors, which make many solvers feel the serious sunk cost. They believe that participating in other activities at the same time may bring more returns and benefits, which also reduces the willingness to participate in the SMEs CCI to a certain extent. From above, CCI platform or SMEs should adopt flexible and diverse incentive models. Differentiated rewards can be set according to the complexity of crowdsourcing tasks and the number of solvers, and the "winner-takes-all" model should not be adopted entirely. In addition, the crowdsourcing platform should minimise the intellectual property disputes of the crowdsourcing achievements and increase solvers' trust in the scheme selection mechanism.

Finding (4): When deciding whether to participate in SMEs CCI, solvers will compare and analyse the perceived benefit equivalent and risk equivalent to measure the net utility brought by participation. If they feel that the sum of the acquired material and non-material benefit is higher than the cost paid, they will actively participate; otherwise, their willingness to participate will be greatly weakened. The path graph shows that the path coefficient (0.764) of benefit perception to participation intention is higher than that (0.173) of cost perception. This indicates that when solvers feel the same actual benefits and costs, the benefit is higher than the cost, and solvers still tend to participate in crowdsourcing. That is to say, the solvers have a strong subjective initiative to crowdsourcing contest, and they are sensitive to interests, which reflects the characteristics of weak cost avoidance. In general, the probability of participating in SMEs CCIs is higher than that of not participating in it.

Finding (5): Whether solvers can continue to participate in SMEs CCI is not only affected by the willingness to participate, but also by the positive effect of the platform's ease of use, which is consistent with the conclusions of the research of Brabham (2010) and Deci, Ryan and Koestner (1999). The empirical results show that the crowdsourcing platform – Zbj.com has been relatively mature at present, and regular test feedback and maintenance mechanisms have been established in terms of technology. Therefore, the solvers' friendly operating system design and other aspects of the crowdsourcing platform are relatively satisfactory, and solvers' continuous participation behaviour is relatively high.

2.6 Conclusions

Based on the social exchange theory, this chapter summarises the benefit perception factors and cost perception factors that affect solvers' participation in SMEs CCI, and proposes a conceptual model of solvers' participation motivation and continuous participation behaviour. The conceptual model is empirically tested by using structural equation method, and the significance and degree of the influence of various motivation factors on the willingness to participate are analysed (Figure 2- 2). The main positive and negative motivation factors are extracted to provide support for the design of incentive mechanism.

Key learnings from this chapter are:

- The findings support the research of Ye and Kankanhalli (2017) to a certain extent.

- Social attribution does not significantly increase the interest perception of solvers.

- Among the cost perception factors, there is uncertainty in the role of the complexity of crowdsourcing tasks, and the risks of intellectual property rights and resource waste have a high path coefficient and significance for cost perception.

● The continuous participation of solvers in SMEs CCI is affected by the net utility determined by the benefit and cost, as well as the positive effect of the ease of use of the crowdsourcing platform. Therefore, crowdsourcing platforms and SMEs should clarify the role of non-material factors such as knowledge acquisition and sharing, reputation in crowdsourcing participation, design incentive mechanisms that combine material and non-material factors, and fully consider the impact of various risks on each solver.

● The design of the incentive mechanisms of SMEs crowdsourcing contest innovation should be based on solvers' participation motives. By referring to social exchange theory, empirical study is done to find out solvers' motivations. The subsequent research on incentive mechanism design will take the above research results as references.

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3 MATERIAL INCENTIVE MECHANISM OF SMES CROWDSOURCING CONTEST INNOVATION

Abstract

When crowdsourcing tasks become complex and difficult to manage, it is not uncommon for a project manager within an SME to consider adopting a 'modularised' approach, delegating responsibility amongst the team (i.e. encouraging crowdsourcees/solvers to cooperate) to simplify the process and increase innovation performance. Principal-agent theory is used to design the material incentive mechanism of SMEs crowdsourcing contest innovation (CCI). Two kinds of material incentive mechanisms based on team total performance (TR) and individual performance (NR) are defined. The principal-agent models of incentive mechanism are constructed and solved, and the impact of task complexity (i.e. retained task volume), collaboration effect, solvers' risk preference and the number of solvers on the effectiveness of the two incentive mechanisms - TR and NR - are discussed and compared in detail.

The results show that when the retained task volume is low, the self-interest effort and altruistic effort of solvers are all positively related to the task collaboration effect, but negatively correlated with the number of solvers and the solvers' risk preference degree; otherwise, the results are the opposite. It is also found that the NR model does not result in any altruistic efforts. As a result, its performance is lower than that of the TR model, and solvers prefer the TR model. However, whether seekers (i.e. SMEs or crowdsourcers) prefer the TR model depends on the retained task volume. According to the research results, it is suggested that SMEs and the crowdsourcing platform should encourage solvers to participate in crowdsourcing contest innovation in the form of team collaboration and implement material reward based on team performance. In addition, it is necessary to pay attention to the risk aversion psychology of solvers and the cooperation effect among task modules.

Keywords: crowdsourcing team collaboration; risk preference; altruistic efforts; principal-agent theory; material performance incentive

3.1 Introduction

The rise and development of Internet technology makes the implementation cost of crowdsourcing contest innovation (CCI) very low. However, the failure of crowdsourcing is not rare. Only by providing appropriate incentives to the solvers (i.e. crowdsourcees who offer services to crowdsourcing problems), can solvers be encouraged to give full play to their collective wisdom to complete tasks more efficiently (Agafonovas, 2013). Therefore, the key to achieving group collaboration through crowdsourcing is to build team collaboration incentives (Bloodgood, 2013). The existing incentive mechanism for crowdsourcing innovation is mainly based on the principal-agent model. Tian, Deng and Fei (2016) designed a material incentive mechanism under the "winner-takes-all" feature of CCI and found that the bidding mechanism can achieve the incentive goal better than the fixed reward mechanism; while Wang *et al.* (2017) found that social incentives can motivate the solvers to continue to make valuable contributions in a dynamic environment. Gao, Chen and Liu (2015) designed a reward consensus mechanism and accurate reward mechanism under the framework of a principal-agent mechanism based on the utility maximisation model to encourage solvers to provide higher-quality solutions. However, Mason and Watts (2010) found that although material incentives can increase the number of tasks completed, they cannot guarantee the quality of work undertaken.

The above research does not consider the problem of team collaboration incentive, paying little attention to the risks in the process of crowdsourcing innovation and, thus, fail to provide effective high-quality solutions to complex CCI tasks or explore the impact of the solver's risk aversion on incentive performance.

In practice, the crowdsourcing contest becomes more competitive after its initial stage. Arguably, experienced solvers are acutely aware of the challenges, risks, and rewards of conducting business via the Internet. It is not uncommon to see crowdsourcing teams emerge through independent management and mutual collaborative learning to reduce risks and improve the chances of winning success (Dissanayake, Zhang and Gu, 2015). This *'mode'* of collaboration has more obvious advantages when the task requires multi-disciplinary skills, because it can achieve good external knowledge connectivity through altruistic efforts between solvers, in order to improve crowdsourcing innovation performance (Ye and Zhu, 2012). This can be seen in the "challenge" type task in InnoCentive, which has set up "team project rooms" (Lakhani and Lonstein, 2011) to facilitate collaboration and communication (Sun *et al.*, 2019). So, what kind of material incentive mechanism should be designed in the collaborative CCI to stimulate solvers to increase more self-interest efforts and altruistic efforts? How does it influence the performance of crowdsourcing tasks and the economic benefits of crowdsourcing subjects? What is the impact of task complexity, risk aversion, and number of solvers on the effectiveness of the incentive mechanism? These problems are the scientific problems that must be considered in the design of the incentive mechanism.

Two performance incentive mechanisms of collaborative CCI are going to be designed, and how team innovation performance is impacted by incentive mechanisms will be revealed through principal-agent modelling. Furthermore, reasons will be provided as to why solvers are encouraged to congregate via online communities and form CCI teams to participate in tasks issued by SMEs. In addition, this chapter examines the regulating effect of task on the incentive mechanism and, theoretically, explains why the increase of retained task volume (namely task complexity) of SMEs CCI is conducive to stimulating higher innovation efforts to create higher innovation performance under team cooperation. Furthermore, the effective conditions of the incentives are solved quantitatively. Obviously, from the perspective of the incentive mechanism, this chapter provides an effective solution for solving complex crowdsourcing (or modularised) tasks, which not only expands the application scope of team cooperation, but also enriches the incentive theory of motivation.

3.2 Problem Description and Basic Assumptions

This chapter analyses a SMEs CCI task composed of one seeker and a collaborative team consisting of $n\,(n \geq 2)$ solvers, and other individual solvers.

SMEs, as the seeker, publish the basic attributes and target requirements of the task on crowdsourcing platforms (self-built platforms or third-party platforms), and decompose the entire task into n modules with certain technical relevance. n solvers are allowed to collaborate on a work platform with a good interactive atmosphere, and participate in CCI as a team, which help to reduce task complexity, use knowledge resources effectively, and improve task quality (Ye and Zhu, 2012). Based on the characteristics of a collaborative team, this chapter divides the efforts of the solver i $(i = 1,2, \ldots, N)$ from the team (hereinafter referred to as the solver) into two parts: self-interest efforts e_i and altruistic efforts E_{ij} . e_i is the effort to complete the solver's own task; E_{ij} represents the efforts of the solver i to improve the performance of the solver j, $(j = 1,2, \ldots, N)$, and e_i and E_{ij} are mutually independent. Therefore, the performance output y_i of the solver i (that is, the performance of module which the solver i undertakes) can be expressed as:

$$y_i = e_i + \sum_{j=1, j\neq i}^{N} E_{ji} + E_i \tag{3-1}$$

$E_i \sim N(0, a^2)$, which represents the uncertainty of the performance, $E_1, E_2, \ldots, E_n$ are mutually independent. Therefore, the total performance Y of the CCI task completed by the collaborative solvers' team can be expressed as:

$$Y = x_0 \sum_{i=1}^{N} y_i = x_0 \sum_{i=1}^{N} \left(e_i + \sum_{j=1, j\neq i}^{N} E_{ji} + E_i \right) \tag{3-2}$$

x_0 represents the collaboration effect among task modules, that is, the ratio of the task's total output to the output of each module (undertaken by individual solvers), which is mainly affected by the degree of knowledge-sharing among the solvers and the integration among the modules. $x_0 > 1$ is called the positive cooperation effect, and $x_0 < 1$ is the negative cooperation effect. It should be pointed out that this chapter believes that knowledge-sharing and module integration do not necessarily lead to altruistic collaborative behaviour, that is, x_0 and E_{ij} are not related.

This chapter proposes to design a participation mechanism whereby the feature of participation is sure to be rewarded, which combines fixed reward, total performance reward and individual performance reward; that is, the awards of the winning team are related to their performance level, and they are not a fixed amount. It is also anticipated that in SMEs CCI, the task performance of the collaborative team is much higher than that of other individual solvers, and the collaborative team has a large probability of winning the crowdsourcing task; hence, the material benefit is directly positively correlated with the crowdsourcing innovation performance. The material benefit obtained by the solver i in the collaborative team can be directly expressed as $w_i = a_i + \{3_i y_i + y_i Y$. a_i is fixed reward, $\{3_i$ is unit reward coefficient based on individual performance, and y_i is the unit reward coefficient based on team performance output. It is clear to see that increasing individual performance output or increasing total performance output can improve the *economic returns* (Brand and Xie, 2010) of solver i.

Other important assumptions used in this chapter are:

(1) The task volume of the crowdsourcing task is quantified as Q , which is determined by the nature and complexity of the task itself. It is called the retained task volume, which is the minimum amount the solver's expected total performance output must reach; otherwise the incentive mechanism is invalid. It is shown as follows:

$$E(Y) = x_0 \mathbf{L}_{i=1}^{N} \left(e_i + \mathbf{L}_{j=1,j\neq i}^{N} E_{ji} \right) > Q \qquad \textbf{(3-3)}$$

(2) The solvers are completely homogeneous. Therefore, the fixed reward, the unit reward coefficient of individual performance, and the unit reward coefficient of total performance of each solver are the same, which is $a_1 = a_2 = ... = a_N = a$, $\{3_1 = \{3_1 = ... = \{3_N = \{3$, $y_1 = y_2 = ... = y_N = y$.

(3) The risk preference coefficient of the solvers is p , and $p > 0$ means risk aversion; $p = 0$ means risk neutrality; and $p < 0$ means risk preference. In view

of the many risk preference factors faced by the crowdsourcing platform, it is assumed $p > 0$ that the solver is risk averse and, also, that the seeker is risk neutral.

(4) The two types of effort costs of the solvers are positively correlated with the degree of effort, and meet the law of increasing marginal effort cost, that is $\frac{\partial c_i}{\partial e_i} > 0, \frac{\partial c_i^2}{\partial^2 e_i} > 0, \frac{\partial c_i}{\partial E_{ij}} > 0, \frac{\partial c_i^2}{\partial^2 E_{ij}} > 0$. For the convenience of discussion, the coefficients of the two types of effort are both supposed to be k. The total effort cost of the solver i is $c_i = \frac{1}{2} k \left(e_i^2 + \sum_{j=1, j \neq i}^{N} E_{ij}^2 \right)$.

(5) There is information asymmetry between the seeker and the solvers. Due to the opacity of the crowdsourcing platform, the seeker can only infer the actual effort of the solvers by observing their performance output (the quality of the solution). Other information is common knowledge. Wang *et al*. (2016) and Tian, Deng and Fei (2016) have made similar assumptions.

Two material incentive mechanisms are designed based on the total performance output (TR) of the collaborative team and the individual performance output (NR) of the solvers. The incentive flow chart is shown in Figure 3- 1. The following is an in-depth discussion of the effects of these two incentive mechanisms, and a comparative analysis.

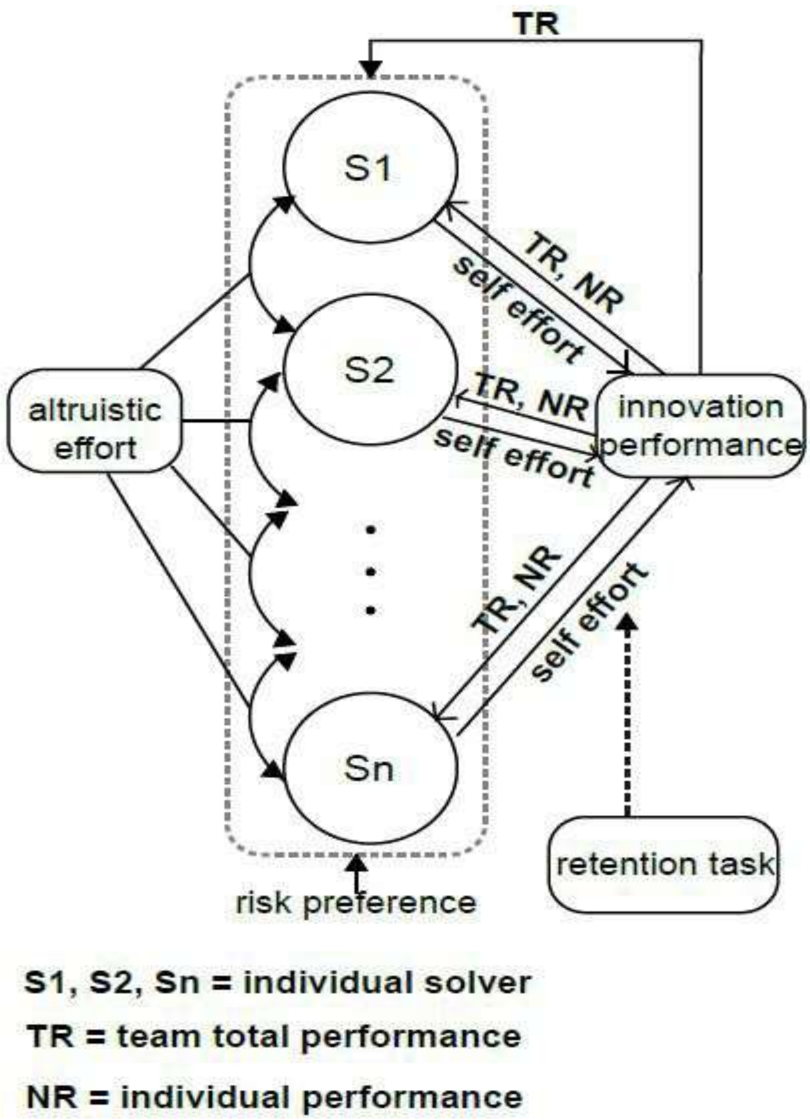

Figure 3- 1 Flowchart of TR and NR incentive models

(designed by the author)

3.3 Methods

Principal-agent theory combined with game theory is used to build up and solve models of TR and NR incentive mechanisms. Further, based on the results of the model solutions, the influencing factors of incentive mechanism performance are analysed. The specific steps are as follows:

Step 1: Constructing the incentive objective functions of the seeker (the principal) and the solver (the agent). The goal of the seeker is to maximise the net income, that is, to maximise the difference between the expected performance of the crowdsourcing task and the total incentive cost (including fixed reward expenditure and performance reward expenditure). The solver is risk averse and its goal is to maximise utility. Utility is expressed as the difference between expected net income and risk cost. The expected net income of the solver is incentive income (including fixed reward and performance reward) minus the cost of innovation effort (including cost of self-interested effort and cost of altruistic effort). The risk cost is expressed as the product of the risk aversion coefficient and the variance of the solver's net income.

Step 2: Determining the decision variables of the seeker and the solver and model constraints. The decision variables of the seeker are the incentive coefficient based on individual performance (β), the incentive coefficient based on team performance (γ) and the fixed reward (α); the decision variables of the solver are self-interested effort (e_i) and altruistic effort (E_{ij}). The model constraint is that the total performance of the solver shall not be lower than the amount of retained task for the task.

Step 3: Determining the game sequence of the two parties. The seeker is the leader, and the solver is the follower.

Step 4: According to the reverse induction method, the decisions of the solver are solved firstly. Considering the incentive constraints, by adopting the first-order partial derivative joint solution method, the expressions for e_i and E_{ij} are obtained in terms of β , γ , α or reaction functions. In order to ensure the maximisation of the objective function, the Hessian matrix test is required.

Step 5: Solving the decisions of the seeker. First, obtaining the response function of fixed reward α according to the compatibility constraint condition. Second, substituting the expressions of e_i , E_{ij} , α into the objective function of the seeker so that the objective function contains only its decision variables β and γ . Third, constructing the Lagrangian function of the decision-making problem of the seeker according to the extremum solution with constraints. Fourth, considering the conditions when the Lagrange factors are zero and nonzero, the first partial derivative method is used to solve the decision variables β and γ in the cases of task constraint and non-task constraint.

Step 6: Displaying of model results. According to the solution results of β and γ, as well as the specific forms of each reaction function, the concrete expressions of each decision variable are obtained by the substitution method, and the expressions of crowdsourcing task performance and economic benefits of both the seeker and the solver are further obtained.

Step 7: Analysis of model results. According to the expression of each decision variable and performance variable, the sensitivity analysis method (sign judgment of the first-order partial derivative) is adopted to analyse the specific influence of each factor on the decision variable and performance variable. By using the difference method, compare and analyse the sizes of decision variables and performance variables under the two incentive mechanism models.

Step 8: Numerical simulation. If the expressions of some variables are too complicated to be directly analysed by sensitivity analysis or the difference method, numerical examples and computer simulation methods are used to obtain more intuitive results.

Step 9: According to the analysis of the model results, determining the management implications.

3.4 Construction and Solution of TR Model

With reference to the description in the previous section, under this incentive mechanism, the net income of the solver includes three parts: personal fixed reward, individual performance reward and team performance reward:

$$\pi_i = w_i - c_i = a + \beta\left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji} + E_i\right) + \gamma x_0 \sum_{i=1}^{N}\left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji} + E_i\right) - \frac{1}{2}k\left(e_i^2 + \sum_{j=1,j\neq i}^{N} E_{ij}^2\right) \tag{3-4}$$

When the solver has a risk preference, the goal of decision making is utility maximisation. Referring to the research by Lu *et al*. (2016), the utility is the expected net benefit minus the negative risk utility. Therefore, the deterministic equivalent return (i.e. economic benefit) of the solver is:

$$
\begin{aligned}
cE_i = a + \beta\left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji}\right) \\
+ yx_0 \sum_{i=1}^{N}\left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji}\right) - \frac{1}{2}k\left(e_i^2 + \sum_{j=1,j\neq i}^{N} E_{ij}^2\right) \\
- \frac{1}{2}pa^2\left(\beta^2 + Ny^2x_0^2\right)
\end{aligned}
\qquad (3\text{-}5)
$$

The goal of the seeker is to maximise the net economic benefits (i.e. the difference between the total performance output of crowdsourcing and the cost of incentives), which can be expressed as:

$$
cM = E\left(Y - \sum_{i=1}^{N} w_i\right) = (x_0 - Nyx_0 - \beta)\sum_{i=1}^{N}\left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji}\right) - Na \qquad (3\text{-}6)
$$

Further, considering the constraint that the total performance output of collaborative crowdsourcing must not be less than the retained task volume, the TR incentive mechanism model can be expressed as:

$$
\max_{\beta,y,e_i,E_{ij}} cM
$$

$$
s.t.\ x_0 \sum_{i=1}^{N}\left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji}\right) \geq Q \qquad (3\text{-}7)
$$

$$
(IR)\, cE_i \geq 5
$$

$$
(Ic)(e_i, E_{ij}) \in \max cE_i
$$

5 is the retained utility of the solver. Since the seeker is the task initiator and incentive leader, the game sequence is: (1) the seeker decides β and y; (2) the solver decides e_i and E_{ij} . Following the method of Steps 4-6, the equilibrium solution of the TR model is obtained, which is shown in Table 3-1.

3.5 Construction and Solution of NR Model

Under the NR model, only fixed rewards and individual performance rewards are considered. The net income of solver i can be expressed as:

$$\pi_i = w_i - c_i = \alpha + \beta\left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji} + \varepsilon_i\right) - \frac{1}{2}k\left(e_i^2 + \sum_{j=1,j\neq i}^{N} E_{ij}^2\right) \quad (3\text{-}8)$$

The deterministic equivalent income is:

$$cE_i = \alpha + \beta\left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji}\right) - \frac{1}{2}k\left(e_i^2 + \sum_{j=1,j\neq i}^{N} E_{ij}^2\right) - \frac{1}{2}\rho\sigma^2\beta^2 \quad (3\text{-}9)$$

The incentive model is expressed as:

$$\max_{\beta,\gamma,e_i,E_{ij}} cM = (x_0 - \beta)\sum_{i=1}^{N}\left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji}\right) - N\alpha \quad (3\text{-}10)$$

$$s.t.\ x_0 \sum_{i=1}^{N}(e_i + \sum_{j=1,j\neq i}^{N} E_{ji}) \geq \bar{Q}$$

$$(IR) cE_i \geq \bar{\omega}$$

$$(Ic)(e_i, E_{ij}) \in \max cE_i$$

The game order and model solving process are similar to the TR model, and the equilibrium results of the model are also presented in Table 3-1.

Table 3- 1 The equilibrium solution of TR and NR models

	NR model		TR model	
	$Q < \frac{Nx_0^2}{(1+b)k}$ ($\lambda = 0$, marked as NR)	$Q > \frac{Nx_0^2}{(1+b)k}$ ($\lambda > 0$, marked as NR1)	$Q < \frac{N^2x_0^2(N-1+(N+1)b)}{((1+b)^2N-1)k}$ ($\lambda = 0$, marked as TR)	$Q > \frac{N^2x_0^2(N-1+(N+1)b)}{((1+b)^2N-1)k}$ ($\lambda > 0$, marked as TR1)
e_i^*	$\frac{x_0}{(1+b)k}$	$\frac{Q}{Nx_0}$	$\frac{((1+2b)N-1)x_0}{((1+b)^2N-1)k}$	$\frac{((1+b)N+b-1)Qk-N(N-1)^2x_0^2}{Nx_0(2bN+N-1)k}$
E_{ij}^*	0	0	$\frac{((1+b)N-1)x_0}{((1+b)^2N-1)k}$	$\frac{bQk+N(N-1)x_0^2}{Nx_0(2bN+N-1)k}$
β^*	$\frac{x_0}{(1+b)}$	$\frac{kQ}{Nx_0}$	$\frac{bx_0N}{(1+b)^2N-1}$	$\frac{((1+b)N-1)Qk-N^2(N-1)x_0^2}{Nx_0(2bN+N-1)}$
y^*	0	0	$\frac{(1+b)N-1}{(1+b)^2N-1}$	$\frac{bQk+N(N-1)x_0^2}{Nx_0^2(2bN+N-1)}$
$E(Y^*)$	$\frac{Nx_0^2}{(1+b)k}$	Q	$\frac{N^2x_0^2(N-1+(N+1)b)}{((1+b)^2N-1)k}$	Q
cM^*	$\frac{Nx_0^2}{2k(1+b)}-N5$	$\frac{2Nx_0^2Q-k(1+b)Q^2}{2Nx_0^2}-N5$	$\frac{N^2x_0^2((1+b)^3N^2+(1+b)(b^2-2)(N+1-b))}{2k((1+b)^2N-1)^2}-N5$	$Q-\frac{N((\beta^*+x_0y^*)^2+(N-1)x_0^2y^2+b(\beta^2+Nx_0^2y^2))}{2k}-N5$

Note: λ is the Lagrange factor under the Karush-Kuhn-Tucker (KKT) conditions (Gordan, G. and Tibshirani, R., 2012).

3.6 Results Analysis of TR Model

This section discusses in detail the influencing factors and action directions of the TR model in the two cases. Firstly, the role of the retained task volume is explored, obtaining Result 1.

Result 1 When $Q < Y^*$, $E(Y^{R*}) > Q$, the TR mechanism is irrelevant with Q; when $Q > Y^*$, $E(Y^{R1*}) = Q$, e_i^{R1*}, E_{ij}^{R1*}, β^{R1*} and y^{R1*} are all positively correlated with Q. $Y^* = \frac{N^2x_0^2(N-1+(N+1)b)}{((1+b)^2N-1)k}$ (b is the risk factor and $b = kpa^2$), hereinafter (i.e. in the following results), the same Y^*.[13]

[13] The proof process of all results in this chapter is presented in Appendix.

Discussion: The result shows that when the retained task volume is higher than that of the crowdsourcing team's optimal total performance output determined by the solver's innovation capacity, can the retained task volume have an incentive effect on the team. The self-interest effort and altruistic effort of the solver will increase as the retained task volume increases, but the premise is that the intensity of the team and individual performance incentive must be improved accordingly. When the retained task volume is less than the optimal total performance output, the task is not difficult to complete, and the target incentive will be useless (each performance indicator is irrelevant with θ).

By describing the conditions for the establishment of the incentive mechanism in Table 3-1, Result 2 is obtained:

Result 2 When $\theta < Y^*$, the condition for the establishment of the incentive mechanism is: $x_0 < \frac{(1+b)^2 N-1}{bN}$; when $\theta > Y^*$, the condition for the establishment of the incentive mechanism is: $\theta < \frac{Nx_0(2bN+N-1+Nx_0(N-1))}{((1+b)N-1)k}$.

Discussion: Result 2 indicates under the scenario of low retained task volume, the collaboration effect among the task modules cannot be too large, otherwise the seeker will have the expectation of being a "free rider" (Grossman and Hart, 1980) and will not implement performance incentives. Otherwise, the excessively high volume of crowdsourcing tasks will greatly increase the incentive cost and the seeker will lose the incentive motivation.

Based on the establishment condition of the incentive mechanism, the influences of the collaborative effect, number of solvers and the risk aversion factor on the incentive effect are discussed, getting Results 3-5.

Result 3 When the conditions for Result 2 are satisfied, it is found: (1) when $\theta < Y^*$, $e_i^{R^*}$, $E_{ij}^{R^*}$, β^{R*} are positively correlated with x_0, y^{R*} is not correlated with x_0, and cM^{R^*} is positively correlated to x_0; (2) when $\theta > \frac{N^2 x_0^2 (N-1+(N+1)b)}{((1+b)^2 N-1)k}$

, $e_i^{R1^*}$, $E_{ij}^{R1^*}$, β^{R1*} are negatively correlated to x_0; when $x_0 < \sqrt{\frac{bQk}{N(N-1)}}$, y^{R1*} is negatively correlated to x_0, when $x_0 > \sqrt{\frac{bQk}{N(N-1)}}$, y^{R1*} is positively correlated to x_0.

Discussion: Result 3 shows that when the retained task volume is low, the collaborative effect among task modules is beneficial to simultaneously improve the two types of efforts of the solver. In return, the seeker is willing to increase the individual performance incentive coefficient, but will not increase the team performance incentive coefficient. When the retained task amount is high, the seeker with information advantages may have an opportunistic behaviour tendency (Yakovleva and Seliverstova, 2016) as the task itself has a strong incentive effect. The seeker will reduce the incentive cost by reducing the unit individual performance reward coefficient, and even the unit team performance reward coefficient, resulting in a decline in the solver's motivation to work.

Result 4 When the conditions stated in Result 2 are met, it is found: (1) when $Q < Y^*$, $e_i^{R^*}$, $E_{ij}^{R^*}$, y^{R*}, α^{R*} are positively correlated to N and β^{R*} is negatively correlated to N; (2) When $Q > Y^*$, $e_i^{R1^*}$, $E_{ij}^{R1^*}$, y^{R1*}, β^{R1*} are all negatively correlated with N.

Discussion: Result 4 shows that when the retained task volume is lower, both the self-interest and altruistic efforts of the solver will increase with the increase in the number of solvers. Additionally, on the one hand, the seeker will strengthen the unit team performance reward coefficient to improve the collaborative (altruistic) efforts among the solvers and improve the task performance; on the other hand, the seeker will appropriately reduce the unit individual performance reward coefficient to reduce incentive costs.

When the retained task volume is higher (than the optimal team performance output), more solvers can obviously reduce the difficulty of achieving the goal. The rational seeker will reduce the intensity of both types of performance incentives at the same time with leeway, which will undoubtedly reduce the effort of the solver. Therefore, from the perspective of incentive effect, in tasks with lower retained task volume, the seeker should strengthen the idea of "crowdsourcing modularity": through the refinement of crowdsourcing modules, attracting more solvers and expanding the scope of crowdsourcing audiences. In tasks with high task requirements, the task should not be too modularised. The seeker should pay attention to the role of target incentives and can fully tap the innovation potential of each solver by appropriately reducing crowdsourcing modules.

Result 5 When the conditions stated in Result 2 are met, it is found: (1) when $\theta < \gamma^*$, $e_i^{R^*}$, $E_{ij}^{R^*}$, γ^{R*} are all negatively correlated to b; when $b < \sqrt{\frac{N-1}{N}}$, β^{R*} is positively correlated to b, when $b > \sqrt{\frac{N-1}{N}}$, β^{R*} is negatively correlated to b; (2) when $\theta > \gamma^*$, $E_{ij}^{R1^*}$, γ^{R1*} are both negatively correlated to b, β^{R1*} and $e_i^{R1^*}$ are positively correlated to b.

Discussion: Result 5 reveals the impact of the solvers' risk preference on the incentive effect of the crowdsourcing contest task. First, the risk preference will drive the solver to cut down the altruistic efforts, leading to the reduction of the unit team performance reward coefficient of the seeker. Therefore, the uncertainty of the task itself will definitely increase the cost of the seeker and reduce seeker's motivation for team incentive. The relationship between the risk preference and the self-interested effort of the solvers depends on the retained task volume. When the volume is high, the risk preference and the self-interested effort are always positively related and the external manifestation of risk preference is "selfishness" (i.e. altruistic efforts are reduced, self-interested efforts are improved). When the retained task volume is low, maximising economic benefits is the main goal of the solver. Since the increase of the unit individual performance reward coefficient is not enough to offset the cost of risk, the solver's efforts are reduced. So, in this scenario, the external manifestation of risk preference is "laziness" (i.e. at the same time, both of the altruistic and self-serving efforts are reduced).

3.7 Results Analysis of NR Model

Result 6 (1) If $\theta < \frac{Nx_0^2}{(1+b)k}$, β^{NR^*}, $e_1^{NR^*}$, πM^{NR^*} are positively related to x_0, negatively related to b, and only πM^{NR*} is positively related to N. And all of β^{NR*}, $e_1^{NR^*}$, πM^{NR^*} are not related to θ; (2) If $\theta > \frac{Nx_0^2}{(1+b)k}$, β^{NR^*}, $e_1^{NR^*}$, πM^{NR^*} are all negatively related to x_0, negatively related to N , and only πM^{NR*} is negatively related to b. And both β^{NR*}, $e_1^{NR^*}$ are positively related to θ.

Discussion: Result 6 shows that similar to the TR model, the incentive effect of the NR model is also regulated by the retained task volume. When the retained task volume is lower, the individual effort level of the solver, the performance incentive intensity of the seeker, and the net income all increase with the enhancement of the collaborative effect and decrease with the increase of the risk preference. The increase of the solver’s number can increase the net economic income of the seeker, but will not improve the solver’s efforts, nor will it change the unit individual performance reward coefficient set by the seeker. This is significantly different from the TR model, which further indicates that the NR model will not lead altruistic behaviour of solvers; hence it is not conducive to the improvement of the overall task performance.

When the retained task volume is higher, the target incentive effect will also be obvious. Under this condition, the increase of collaborative effect and the number of crowdsourcing modules will allow the seeker to have an “opportunity” to reduce the incentive intensity and reduce the incentive cost. Therefore, the level of the solver’s effort and the overall performance are also inversely related to these two factors. Unlike the TR model, the seeker will not change the intensity of performance incentive due to the increase of risk preference in the NR model, which indicates that if the solver has no altruistic behaviour, even if the solver is conservative due to the existence of risk preference, the seeker will not reduce the individual performance reward of the solver for the purpose of completing the task.

3.8 Comparative Analysis of TR Model and NR Model

Result 7 (1) $E\left(Y^{R*}\right) > E\left(Y^{NR*}\right)$; (2) $\beta^{R*} < \beta^{NR*}$, $e_i^{R^*} > e_i^{NR^*}$, $y^{R*} > y^{NR*}$, $E_{ij}^{R^*} > E_{ij}^{NR^*}$; (3) $\beta^{R1^*} < \beta^{NR1^*}$, $e_i^{R1^*} < e_i^{NR1^*}$, $y^{R1^*} > y^{NR1^*}$, $E_{ij}^{R1^*} > E_{ij}^{NR1^*}$.

Discussion: Result 7 shows that only when the retained task volume is low, can the TR model drive the solver to make more self-interest efforts. When the retained task volume is high, the self-interest effort under the NR model is higher than the TR model for the more intensity of unit individual performance reward. However, because the TR model can stimulate altruistic efforts among team members, it will certainly produce higher crowdsourcing performance than the NR model and has more advantages in completing complex collaborative crowdsourcing tasks. In conclusion, what kind of material performance incentive mechanism should be implemented in collaborative crowdsourcing tasks depends on the task complexity.

3.9 Numerical Simulation

In this part, numerical simulation is used to discuss the impact of the risk preference factor b and the number N of the solver on the economic benefits of the seeker under the TR model, and compares the results with the NR model to reveal the economic motivation of the seeker for implementing incentives. Setting $k = 1, x_0 = 1.2, 5 = 0.1$. First, a graph is drawn up of the impact of b and N on the deterministic equivalent income cM when the retained task volume is low, and is shown in Figure 3-2.

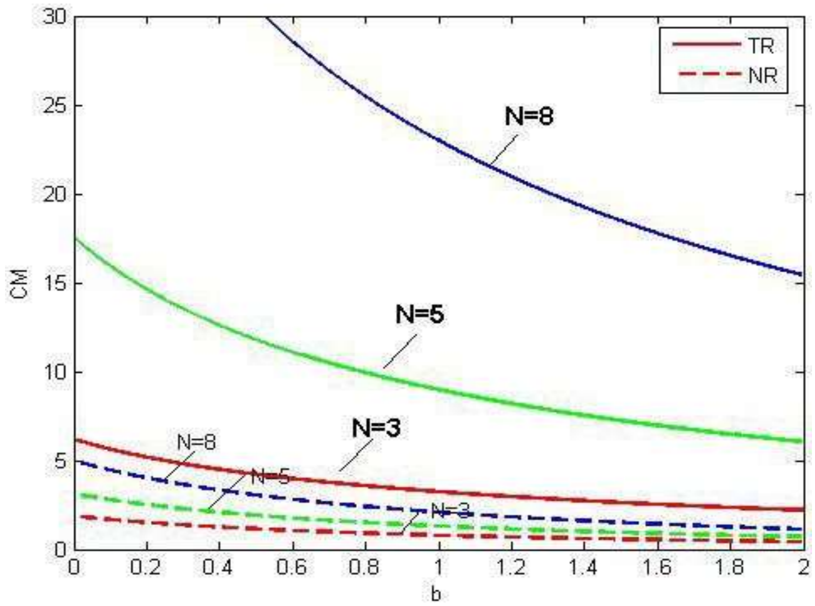

Figure 3- 2 Seeker's deterministic equivalent income ($\varrho < min\left\{\frac{N^2x_0^2(N-1+(N+1)b)}{((1+b)^2N-1)k}, \frac{Nx_0^2}{(1+b)k}\right\}$)

From Figure 3- 2, without the constraint of the retained task volume, no matter which incentive model is adopted and no matter how many solvers there are, the seekers' deterministic economic returns are bound to decrease with the increase of risk preference factors. This shows that the higher the risk preference of the solver, the lower the seekers' economic motivation of the performance incentive implementation. In addition, it can be seen that the larger the N, the higher the curve's position, indicating that increase in the number of the solvers (or the number of task modules) is also conducive to improving economic profits. The seeker has the motivation to deepen the "modularity", which verifies Result 4 of this chapter. However, the graph also shows that the greater the N , the faster the downward trend of the curve, indicating that the negative effect of risk preference on the seeker's benefit income will accumulate with the increase of the solver number. Hence, the seeker should try to reduce the risk preference of the solver that causes performance uncertainty instead of decomposing crowdsourcing tasks blindly. Finally, from the perspective of economic benefits, the seeker always prefers the TR incentive model in the case of lower retained task volume, regardless of the risk preference of the solver.

The following analyses the situation where the total equilibrium output under the TR model is lower than the retained task volume ($Q > \frac{N^2 x_0^2 (N-1+(N+1)b)}{((1+b)^2 N-1)k}$) (the analysis of the NR model is similar). Setting $N = 5$, analysing the impact of Q and b in the feasible region (the area where the incentive mechanism is established) on cM. Results are shown in Figure 3-3.

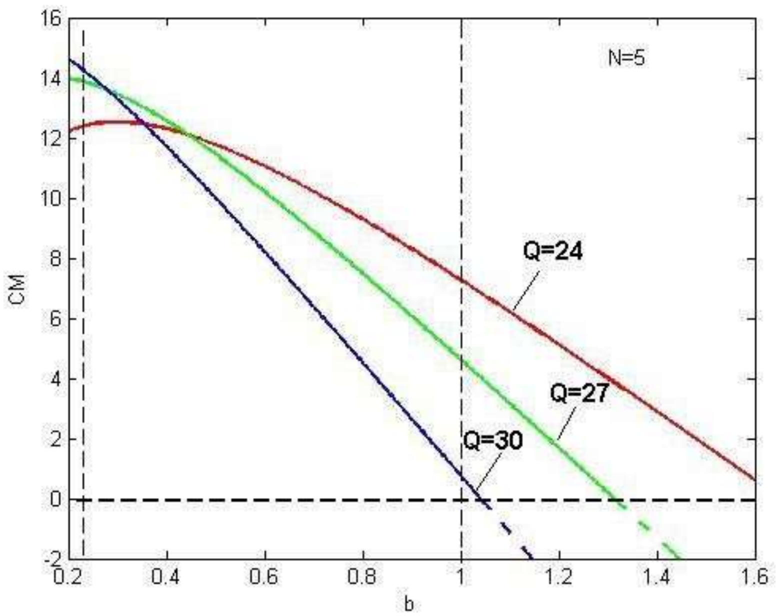

Figure 3-3 Seeker's deterministic equivalent benefit under TR mode ($Q > \frac{N^2 x_0^2 (N-1+(N+1)b)}{((1+b)^2 N-1)k}$)

It can be seen from Figure 3- 3 that the three curves are in a downward trend, indicating that when the retained task volume is high, the deterministic economic returns of the seeker will decrease with the increase of the risk preference factor, and the downward trend speed will be faster and faster until the economic motivation for implementing collaborative incentives is completely lost ($cM^{R*} < 0$). In addition, it is found that the larger Q is, the faster the corresponding curve declines. Combined with Result 1 of this chapter, it is known that when the risk preference factor is small, the crowdsourcing task with high retained task volume will incentivise the solver to make greater efforts to achieve higher goals, so that the seeker can obtain more significant deterministic economic benefits. When the risk preference factor is high, the solver's risk preference and the risk cost brought by the task uncertainty will offset the benefits brought by performance output. Therefore, for the seeker, it is necessary to balance the target incentives and risk costs.

3.10 Research Limitations, Reflection and Contribution of Knowledge in Modelling

3.10.1 Research Limitations

● The incentive mechanism is only considered in a single task stage. To make the findings more valid, it is considerable to explore whether the mechanism can still achieve performance maximisation in multiple related task stages.

● The impact of seeker's risk preference on task performance and economic benefits is not discussed in this research.

● The incentive process and the performance of the incentive mechanisms are analysed. However, whether the results meet the practical situation needs to be verified.

3.10.2 Reflection

In response to the questions posed in the Introduction:

<u>Question 1:</u> What kind of material incentive mechanism should be designed in the collaborative CCI to stimulate solvers to increase more self-interest efforts and altruistic efforts?

A linear '*performance'* incentive mechanism which is based on both the team performance and individual performance can the seeker stimulate solvers to increase more self-interest efforts and altruistic efforts. It works better than the fixed reward mechanism.

Question 2: How does the material incentive mechanism influence the performance of crowdsourcing tasks and the economic benefits of crowdsourcing subjects?

The application of TR model can stimulate not only the self-interest efforts but also the altruism efforts of the solvers. With the joint effect of these two kinds of efforts, a higher task performance and economic value can be achieved despite more incentive costs.

Question 3: What is the impact of task complexity, risk aversion, and number of solvers on the effectiveness of the incentive mechanism?

Risk aversion, the number of solvers both have direct impact on the effectiveness of the incentive mechanism, but whether the impact is positive or negative, it is largely decided by task complexity.

In response to how this research could be advanced in the future:

It is believed that the designed 'material' incentive mechanisms can provide useful practical implications for SMEs when issuing complicated CCI tasks in the future. For researchers who are interested in this study, there are four recommended research directions in the future:

- How to decompose difficult tasks and integrate solutions into one proposal?
- How to encourage solves to participate in SMEs CCI as a team?
- How do SMEs manage to find a proper technique to measure the solver's individual performance and team performance so as to implement the performance incentive?
- How do SMEs filter the solvers who have strong risk aversion psychology when issuing tasks?

3.10.3 Contribution of Knowledge in Modelling

The model is designed for SMEs using CCI, i.e. issuing crowdsourcing contest tasks on online platforms in order to solve their internal innovation problems.

The challenges and the contributions of the mathematical model set up in this chapter relies in following parts:

- Putting a competitive and cooperative relationship between solvers into the model
- Considering the constraint effect of the retained task in order to make the theoretical model closer to the actual situation
- Quantifying psychological factors (risk adverse) into the mathematical model

3.11 Conclusions

According to the character of the crowdsourcing contest carried out in the form of team collaboration, an incentive mechanism based on the team's total performance (TR) and an incentive mechanism based on individual performance (NR) are designed and modeled, respectively, in this chapter. The detailed comparative study is carried out, and the research results are verified by numerical simulation. Findings show that only when the retained task volume (the complexity of the crowdsourcing task) is high enough, can the task itself generate a positive incentive effect in both mechanisms. Specifically, in the TR model, when the retained task volume is lower than a certain threshold, the self-interest and altruistic efforts of the solver increase with the enhancement of the collaborative effect and the increase of the number of solvers, but decrease with the increase of the risk preference. Otherwise, both of the two types of efforts' decrease have the opposite effect, and the risk preference factor will increase self-interested effort, but will reduce altruistic effort. However, in the NR model, the solvers will not produce altruistic effort, but will be stimulated to increase their self-interest effort than in the TR mechanism under the high retained task volume. It is also found that from the perspective of economic benefit, the seeker prefers the TR mechanism, as it produces a better crowdsourcing performance than the NR mechanism when the retained task volume is high. However, when retained task volume is low, the result will be uncertain.

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4 DYNAMIC REPUTATION INCENTIVE MECHANISM OF SMES CROWDSOURCING CONTEST INNOVATION

Abstract

Reputation is an important non-material motivation factor and is conducive to forming long-term stable innovation performance of SMEs crowdsourcing contest innovation (CCI). In order to review the incentive effect of reputation on innovation efforts, a two-stage dynamic performance incentive model combining reputation and material reward is designed considering the characteristics of "winner-takes-all" of a crowdsourcing contest. Also, the influences of the explicit reputation correction coefficient, implicit reputation coefficient and the number of solvers (i.e. crowdsourcees) on the incentive effect are discussed. In addition, the incentive effect of both the reputation incentive mechanism and the non-reputation incentive mechanism are compared.

The result shows that although the increase of the implicit reputation coefficient helps to improve the level of solvers' effort at each task stage (Stage 1 and Stage 2), the uncertainty of explicit reputation decreases the effort in the second task stage and results in a certain ratchet effect (weakening the incentive effect). Under the reputation incentive mechanism, solvers' effort, innovation performance must be higher but unit performance reward must be lower in Stage 2 than that of the non-reputation incentive mechanism, but contains uncertainty in Stage 1. It is also found that the increase in the number of solvers enhances solvers' bargaining ability and weakens the ratchet effect in Stage 1 but decreases the positive value of the reputation mechanism. According to the research results, it is suggested that it is necessary to establish and refine the dynamic reputation evaluation system to decrease the uncertainty of explicit reputation. Meanwhile, the crowdsourcing platform should provide a full skills training service in order to comprehensively promote solvers' skills and improve the implicit reputation coefficient of solvers.

Keywords: reputation effect; dynamic incentive mechanism; implicit reputation; explicit reputation

4.1 Introduction

Since its development, crowdsourcing innovation has interacted with the concepts of open innovation, open source community, and collective wisdom resulting in different innovation models, such as crowdsourcing contest, collaborative communities, and complementary systems. Compared with large enterprise projects, the size of each single crowdsourcing task issued by SMEs is relatively small, and the reward amount is limited. Therefore, the crowdsourcing contest has become the most popular crowdsourcing model for SMEs, which enables seekers (i.e. crowdsourcers who launch crowdsourcing tasks) to obtain unlimited creative works or high-quality practical products more effectively (Mortara, Ford and Jaeger, 2013). For example, Netflix, through its own crowdsourcing platform, offered a reward of 1 million US dollars for the best suggestions for its movie recommendation system (Johnston, 2012). An effective incentive mechanism is an important factor to improve the quality level of CCI tasks, which has attracted the attention of many scholars, such as Archak and Sundararajan (2009), Megidish and Sela (2013), and Tian, Deng and Fei (2016).

The rapid development of professional online platforms has played a part in the insurgence of crowdsourcing tasks set by SMEs. In practice, some crowdsourcing platforms have begun to pay attention to the relevance of the performance of the solver in their previous tasks, which highlights the importance of another 'latent' element – reputation in the incentive mechanism. For example, in Zbj.com, the Bidwitkey (the solver rewarded for bidding, i.e. through bidding for a crowdsourcing project and winning the bid, the solver obtains the opportunity of project development and finally generates value) began to generally adopt the point ranking system in the bidding process. After authentication, the platform will offer the solver the corresponding points according to the quality of the solution provided by the solver in each task, and set the cumulative points' standard for each level. Regular online members who acquire trusted VIP status are given priority in securing the next task (Lu, 2016). The reputation incentive mechanism mainly relies on public praise (explicit reputation) achieved from the previous tasks and a higher level of effort (implicit incentive). This is more conducive to experienced solvers to win the contest, but also caters to the reputation motivation of the solvers in SMEs CCI. It is of great significance to the realisation of the long-term economic benefits of the solver and the continuous performance improvement of the crowdsourcing task.

Although reputation incentives have been developed in practice in CCI, they have not attracted the attention of many scholars in theory. The reputation incentive and its application in other fields are not uncommon. Kreps and Wilson (1982) studied the incentive effect of reputation by using the repeated game model. By constructing the Kreps-Milgrom-Roberts-Wilson (KMRW) reputation model, it was concluded that the reputation incentive mechanism can achieve the purpose of motivating agents under the condition of multiple repeated principal-agent relationships. Liu and Zhang (2005) and Kong and Zhang (2014) have studied the short-term and long-term dynamic incentive models of Chinese enterprise managers based on the combination of reputation mechanism and explicit mechanism. Besides, Kong and Zhang (2014) also considered the factors of political reputation and market reputation. Xiao and Sheng (2003) established a two-stage reputation model based on the signalling game and studied the reputation's role in the decision of optimal R&D strategies in dynamic environments. Wang *et al.* (2016) established corresponding reputation update methods for free-riding (Grossman and Hart, 1980) problems and false-reporting problems, thereby forming a complete crowdsourcing incentive mechanism. Shi *et al.* (2017) studied the explicit and implicit double reputation incentive mechanism in major engineering prefabrication, indicating that the introduction of the reputation incentive mechanism under certain conditions can better coordinate the cooperative relationship between owners and prefabricators. From the literature, it can be seen that although reputation incentive has achieved certain academic results, it cannot be directly introduced into the incentive mechanism of SMEs CCI. Arguably, this is because CCI has a clear "winner-takes-all" feature, and only the winner can achieve the performance reward. Therefore, the mechanism of reputation effect will be very complex, and the performance of reputation incentive in each task cycle will also face greater uncertainty. Then, for solvers participating in CCI, in order to improve crowdsourcing performance for long task stages, how do seekers integrate explicit and implicit reputation into the design process of the incentive mechanism? How does this dual reputation mechanism affect the innovation efforts made by solvers and the incentive reward paid by seekers in each task stage? Will the task performance and economic benefit of each task stage be really improved? What impact will the size and uncertainty of reputation, as well as the number of solvers, have on the incentive effect of the reputation mechanism? It is believed that these problems have important practical significance for the SMEs CCI.

To answer the above problems, in this chapter, by fully considering the "winner-takes-all" feature, the winning probability of the solver in a single task is defined. By learning from the existing reputation incentive framework, a two-stage dynamic incentive model combining reputation effect and material reward is established. The impact of explicit reputation and implicit reputation is taken into account, and the adjustment effect of the number of solvers on the reputation incentive effect is discussed.

4.2 Model Description and Assumptions

The model considers $N(N \geq 2)$ solvers participating in two consecutive CCI tasks issued by SMEs that belong to a certain '*professional'* field and have certain relevance. The seeker adopts an incentive method combining fixed rewards and performance rewards (Tian, Deng and Fei, 2016), and considers the reputation factor in the incentive mechanism. All solvers who participate in the task can get fixed rewards, but only the solver who submits the best solution can get the performance rewards of the task. Under the reputation mechanism, the performance output of the solver i is determined by its effort level, reputation (public praise) output, and random factors (Shi *et al.*, 2017). It can be expressed as:

$$m_{it} = ke_{it} + \lambda r_{it} + E_{it},\ t = 1,2; i = 1,2, ..., N \qquad \textbf{(4-1)}$$

m_{it} is the performance output of the solver i in the Task t ; k is the effort performance coefficient, representing the performance of the solver's unit effort, which is closely related to the solver's professional ability and work efficiency. e_{it} is the level of effort invested by the solver i in Task t ; λ is the reputation output coefficient of the solver, indicating the solver's ability to convert reputation into task performance; r_{it} is the level of explicit reputation of the solver i in the Task t. Considering the uncertainty of reputation, it is assumed $r_{it} \sim N(a, a^2_r)$, E_{it} represents a random factor that affects the performance output of the solver i, and thus assumes $E_{it} \sim N(0, a^2_E)$.

The information of the seeker and the solver is asymmetric, and the former cannot directly observe the effort of the latter. The seeker has rational expectations. In Task 1, the seeker will estimate the solver i's effort level e^*_{i1} by observing the output m_{i1} of the solver i. While in Task 2, the seeker will revise i's reputation based on e^*_{i1} and m_{i1} . That is, the weighted average of the priori expectation value λa and the actual observation value $m_{i1} - k e^*_{i1}$ is used to represent the reputation level of Task 2, which is expressed as:

$$v_i = E(\lambda r_{i2} | m_{i1}) = (1 - r)\lambda a + r(m_{i1} - k e^*_{i1}) \quad \textbf{(4-2)}$$

Similar to the research by Shi *et al.* (2017), the correction coefficient r is the ratio of the explicit reputation output uncertainty of the solver i to the total performance output uncertainty, which is expressed as:

$$r = \frac{\lambda^2 a^2_r}{\lambda^2 a^2_r + a^2_E} \quad \textbf{(4-3)}$$

In other words, the higher the uncertainty of the explicit reputation, the greater the r; hence, the result is:

$$var(v_i) = r^2(\lambda^2 a^2_r + a^2_E) = \lambda^2 r a^2_r \quad \textbf{(4-4)}$$

Generally speaking, $0 < r < 1$. According to the characteristics of CCI, the seeker will adopt the solution with the highest performance output level in each task stage. From the performance output - Equation (4- 1), the probability that the performance of the solver i exceeds that of solver j in Stage t is:

$$r\ b(m_{it} > m_{jt}) = r\ b(k(e_{it} - e_{jt}) > (_t)) = {}_t(k(e_{it} - e_{jt})) \quad \textbf{(4-5)}$$

$$i = 1,2,\dots,n;\ j = 1,2,\dots,n;\ j \neq i;\ t = 1,2;\ \xi_t = \begin{cases} \lambda(r_{jt} - r_{it}) + (\varepsilon_{jt} - \varepsilon_{it}) & t = 1 \\ v_j - v_i + (\varepsilon_{jt} - \varepsilon_{it}) & t = 2 \end{cases}$$

From (4-5), $E(\xi_t) = 0$, $D(\xi_t) = \begin{cases} 2(\lambda^2\sigma_y^2 + \sigma_\varepsilon^2) & t = 1 \\ 2(\lambda^2 r\sigma_y^2 + \sigma_\varepsilon^2) & t = 2 \end{cases}$. $H_t(.)$ and $h_t(.)$ are the distribution function and density function of the joint random variable ξ_t. Assuming that the solvers are homogeneous, the probability equation for the solver i to win in Stage t is:

$$P(e_{it}) = prob(m_{it} \geq \max(m_{1t}, m_{2t}, \dots, m_{nt})) = \frac{2^{n-1}(H_t(k(e_{it} - e_{jt})))^{n-1}}{n} \tag{4-6}$$

Other important assumptions in this chapter are:

(1) In Task t, solver i can receive a fixed bonus a_t. To maximise the solution's quality, the winner's reward is not fixed. Apart from a_t, a performance reward of which the unit reward is β_{it} will also be gained by the winner. Therefore, the expected return of the solver i in Task t can be expressed as:

$$w_{it} = a_t + P(e_{it})\beta_{it}m_{it} = a_t + \frac{2^{n-1}(H_t(k(e_{it} - e_{jt})))^{n-1}}{n}\beta_{it}m_{it} \tag{4-7}$$

(2) Assuming that the revenue conversion rate of the task's performance output is 1, thus the revenue of the seeker is the performance output of the winning solver. The revenue of the seeker in Task t can be expressed as:

$$\begin{aligned} W_t &= \sum_{i=1}^{n} P(e_{it})(1 - \beta_{it})m_{it} - na_t \\ &= \sum_{i=1}^{n} \frac{2^{n-1}\left(H_t\left(k(e_{it} - e_{jt})\right)\right)^{n-1}}{n}(1 - \beta_{it})(ke_{it} + \lambda r_{it} + \varepsilon_{it}) \\ &\quad - na_t \end{aligned} \tag{4-8}$$

(3) The effort cost of the solver is a strictly monotonically increasing the convex function of its effort level, which means $\frac{\partial c}{\partial e} > 0$, $\frac{\partial^2 c}{\partial e^2} > 0$. This chapter also considers the role of implicit reputation. According to the research by Liu and

Zhang (2005), the cost of effort is negatively related to implicit reputation. Therefore, the effort cost of the solver is:

$$C(e_{it}) = \frac{u}{2(1 + e_i)} e_{it}^2 \qquad \textbf{(4-9)}$$

u is the unit effort cost coefficient. $1 + e_i$ is the implicit reputation coefficient of the solver i, which indicates the implicit reputation can be reflected as the cost sharing of the current stage of the task. To simplify the model, it is assumed $e_1 = e_2 = ... = e_n = e$, $1 < 1 + e < 2$ and $\varphi = 1 + e$.

(4) Both the seeker and the solver are risk-neutral, and their decision-making goals are to maximise net income.

According to the above description, the process of the two-stage dual reputation incentive mechanism designed in this chapter is shown in Figure 4- 1. The following is the construction and solution of the incentive mechanism model.

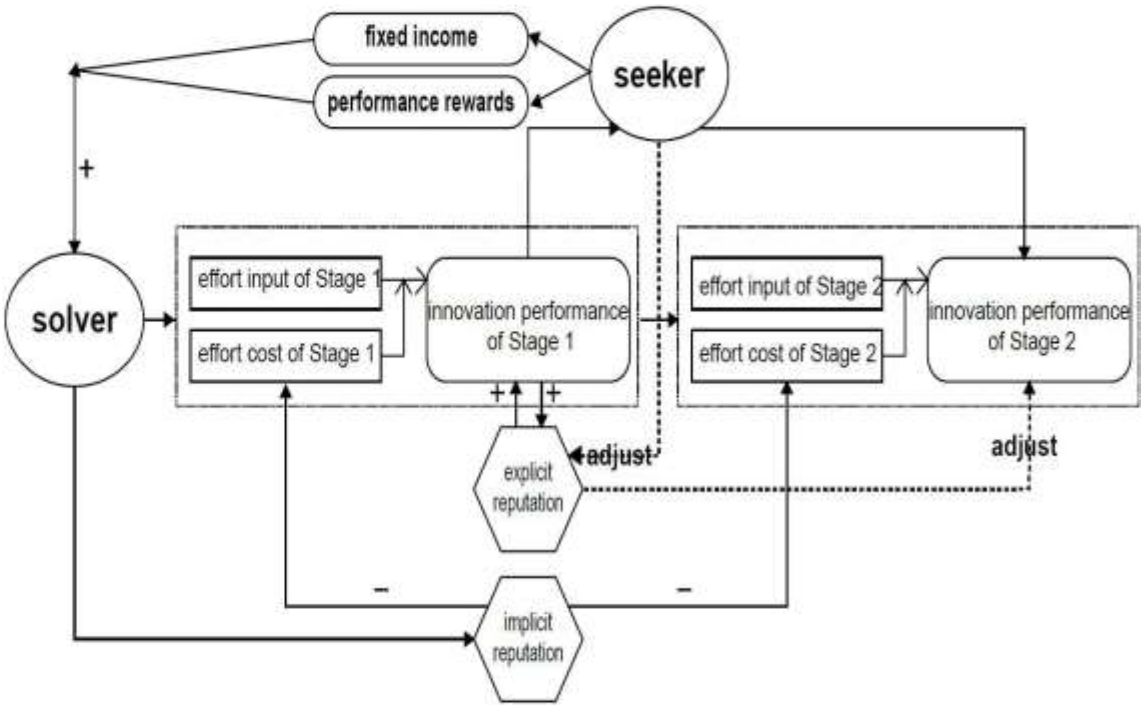

Figure 4- 1 Flowchart of two-stage reputation incentive mechanism of SMEs CCI

(designed by the author)

4.3 Methods

Principal-agent theory combined with game theory is used to solve the model construction and solution of the dual reputation performance incentive mechanism for single-person participation in SMEs CCI with the “winner-takes-all” character. In addition, combined with the model results, the influencing factors and mechanism of the reputation incentive mechanism are discussed. Specific steps are as follows:

Step 1: Determining the expressions of the solver’s expected crowdsourcing performance output for each task cycle/phase. The expressions should at least include the actual effort input and reputation output of the current period.

Step 2: Calculating the winning probability of the solver. The winning probability is based on the performance output, which is expressed as the probability that the performance output of the winning solver is higher than the performance output of all other solvers.

Step 3: Constructing the objective functions of the seeker and the solver in the second task cycle/phase under the dual reputation incentive mechanism. The goal of the seeker is to maximise the expected net income (the difference between the expected total income and the total incentive cost), and the goal of the solver is to maximise the expected net income (the difference between incentive income and innovation cost).

Step 4: Solving the performance incentive model of the second task cycle under the dual reputation mechanism. The details are as follows:

> (4.1) Determining the decision variables of the seeker and the solver, which are the unit performance incentive coefficient β_2 and the level of crowdsourcing effort e_2, respectively.
> (4.2) Determining the game sequence of the two parties: the seeker leads, and the solver follows.
> (4.3) Obtaining the decision of the solver: according to the incentive constraints, the first-order partial derivative method

is used for the objective function of the solver to obtain the expression of e_2.

(4.4) Securing the decision of the seeker: substituting the expression e_2 in the seeker's objective function, and combined with the constraint compatibility conditions, obtaining the expression of the solver's objective function with respect to β_2 , then using the first-order partial derivative method to get the expression of β_2.

(4.5) Substituting the expressions e_2 and β_2 to the incentive model and obtaining the expressions of the task performance and the economic benefits of both the seekers and solvers in the second task phase.

Step 5: Constructing the objective functions of the seeker and the solver in the first task phase under the dual reputation incentive mechanism. The objective function of both the seeker and the solver are the sum of the expected net income of the two task periods. The construction process of the net income expression of the first task period is similar to the second task period.

Step 6: Solving the performance incentive model of the first task cycle under the dual reputation mechanism. The first-order partial derivative method is still used for the solution. The specific process is similar to Step 4.

Step 7: Building and solving the model without reputation incentives. Compared with the reputation incentive mechanism model, the performance output that does not have a reputation incentive is only related to the solver's effort input, and the models of the first and second task cycles are completely consistent. For specific steps, please refer to Steps 3 and 4.

Step 8: Analysis of model results. According to the expressions of decision variables and performance variables, the sensitivity analysis method (the judgment of first-order partial derivative symbols) is used to analyse the influence of explicit reputation coefficient and variance, implicit reputation coefficient and the number of solvers on the two-stage decision variables and performance variables, respectively. Based on the difference method, the value of the reputation incentive mechanism is summarised by comparing and analysing the two-stage decision variables and performance variables under the two incentive models with and without reputation.

Step 9: Numerical simulation. If the expressions of some variables are too complicated to be directly analysed by sensitivity analysis or the difference method, numerical examples and computer simulation methods are used to obtain more intuitive results.

Step 10: According to the analysis of the model results, distributing management implications.

4.4 Reputation Incentive Mechanism of SMEs Crowdsourcing Contest Innovation

The main function of the reputation incentive mechanism is that the performance of the current task period affects the earnings of the future task period, so the reverse induction method is adopted to do the analysis. Hence, the incentive model of the second task stage is firstly studied, followed by study of the first stage.

4.4.1 Construction and Solution of the Performance Incentive Model in the Second Task Phase

According to the description in Section 4.3, the revenue of the solver i in the second task phase can be expressed as:

$$\begin{aligned} w_{i2} &= a_2 + P(e_{i2})\beta_{i2} m_{i2} - c(e_{i2}) \\ &= a_2 + \frac{2^{n-1}\left(_{t}\ \left(k\left(e_{it}-e_{jt}\right)\right)\right)^{n-1}}{n}\beta_{i2}\left(k e_{i2} + \lambda y_{i2} + \varepsilon_{i2}\right) - c(e_{i2}) \end{aligned} \tag{4-10}$$

Substituting the adjusted reputation output into (4-10), then:

$$ _{i2} = a_2 + \frac{2^{n-1}\left(\sum_t \left(k\left(e_{it} - e_{jt}\right)\right)\right)^{n-1}}{n} \beta_{i2}\left(ke_{i2} + v_i\right) - \frac{u}{2\varphi} e_{i2}^2 \quad (4\text{-}11)$$

The deterministic benefits/income of the seeker in Stage 2 can be expressed as:

$$U_2 = \sum_{i=1}^{n} \left[\frac{2^{n-1}\left(\sum_t k\left(e_{it} - e_{jt}\right)\right)^{n-1}}{n} (1 - \beta_{i2})(ke_{i2} + v_i) \right] - na_2 \quad (4\text{-}12)$$

Therefore, the reputation incentive mechanism in Stage 2 is jointly decided by a_2, e_{i2}, β_{i2}. The incentive model is expressed as follows:

$$\max_{a_2, e_{i2}, \beta_{i2}} U_2 = \sum_{i=1}^{n} \left[\frac{2^{n-1}\left(\sum_2 k\left(e_{it} - e_{jt}\right)\right)^{n-1}}{n} (1 - \beta_{i2})(ke_{i2} + v_i) \right] - na_2 \quad (4\text{-}13)$$

$$s.t.\ (IR)\ a_2 + \frac{2^{n-1}\left(\sum_2 k\left(e_{it} - e_{jt}\right)\right)^{n-1}}{n} \beta_{i2}\left(ke_{i2} + v_i\right) - \frac{u}{2\varphi} e_{i2}^2 \geq F_{i2}$$

$$(Ic)\ e_{i2} \in \max \left[a_2 + \frac{2^{n-1}\left(\sum_2 k\left(e_{it} - e_{jt}\right)\right)^{n-1}}{n} \beta_{i2}\left(ke_{i2} + v_i\right) - \frac{u}{2\varphi} e_{i2}^2 \right]$$

$$i = 1,2, \ldots, n$$

The homogeneity of the solver results in $e_{12} = e_{22} = \ldots = e_{n2} = e_2$, $\beta_{12} = \beta_{22} = \ldots = \beta_{n2} = \beta_2$ and $v_1 = v_2 = \ldots = v_n =$, and also $_{12} = {}_{22} = \ldots = {}_{n2} = {}_2$. Since ε_2 follows a normal distribution with mean value 0 and variance value $2\left(\lambda^2 ra_y^2 + a_E^2\right)$, so there are $_2(0) = \frac{1}{2}$ and $h_2(0) = \frac{1}{2\sqrt{\left(\lambda^2 ra_y^2 + a_E^2\right)\pi}}$. F_{i2} is the retained utility of the solver i in the second task stage, and obviously $F_{12} = F_{22} = \ldots = F_{n2} = F_2$. $F_2 = {}_2 = \frac{1(U2+n\ 2)}{n}$. The retained utility is the maximum utility that the solver may gain by participating in the task at the expense of giving up other opportunities. Additionally, in the reputation incentive mechanism, the retained utility is related to the solver's bargaining ability with the seeker, so, 1 represents the bargaining ability of the solver. The equilibrium solution of the second task phase is obtained, which is shown in Table 5.1.

4.4.2 Construction and Solution of the Performance Incentive Model in the First Task Phase

Under the reputation incentive mechanism, the aim of both the seeker and the solver in the first task phase is to maximise the sum of the two-stage deterministic returns. Since the first stage is the initial introduction, the seeker cannot modify the reputation of the solver, so the sum of the two-stage deterministic benefits of the solver is:

$$
\begin{aligned}
{}_i &= {}_{i1} + {}_{i2} \\
&= a_1 + \frac{2^{n-1}{}_1 k\left(\left(e_{it} - e_{jt}\right)\right)^{n-1}}{n} \{3_{i1}(ke_{i1} + \lambda a) - \frac{u}{2<f} e_{i1}^2 \\
&+ a_2 + \frac{2^{n-1}{}_2 k\left(\left(e_{it} - e_{jt}\right)\right)^{n-1}}{n} \{3_{i2}(ke_{i2} + v_i) - \frac{u}{2<f} e_{i2}^2
\end{aligned}
\quad (4\text{-}14)
$$

The sum of the two-stage deterministic benefits of the seeker is:

$$
\begin{aligned}
U = U_1 + U_2 &= \mathbf{L}_{i=1}^{n}\left[\frac{2^{n-1}{}_1 k\left(\left(e_{it} - e_{jt}\right)\right)^{n-1}}{n}(1 - \{3_{i1})(ke_{i1} + \lambda a)\right] - na_1 \\
&+ \mathbf{L}_{i=1}^{n}\left[\frac{2^{n-1}{}_2 k\left(\left(e_{it} - e_{jt}\right)\right)^{n-1}}{n}(1 - \{3_{i2})(ke_{i2} + v_i)\right] - na_2
\end{aligned}
\quad (4\text{-}15)
$$

The optimisation model for Stage 1 is as follows:

$$\max_{a_1,e_{i1},\beta_{i1}} U=\sum_{i=1}^{n}\left[\frac{2^{n-1}\left(k_1\left(e_{it}-e_{jt}\right)\right)^{n-1}}{n}(1-\beta_{i1})(ke_{i1}+\lambda a)\right]-na_1$$
$$+\sum_{i=1}^{n}\left[\frac{2^{n-1}\left(k_2\left(e_{it}-e_{jt}\right)\right)^{n-1}}{n}(1-\beta_{i2})(ke_{i2}+v_i)\right]-na_2 \tag{4-16}$$

$$s.t.\ (IR)\ a_1+\frac{2^{n-1}\left(k_1\left(e_{it}-e_{jt}\right)\right)^{n-1}}{n}\beta_{i1}(ke_{i1}+\lambda a)-\frac{u}{2\varphi}e_{i1}^2+a_2$$
$$+\frac{2^{n-1}\left(k_2\left(e_{it}-e_{jt}\right)\right)^{n-1}}{n}\beta_{i2}(ke_{i2}+v_i)-\frac{u}{2\varphi}e_{i2}^2\geq F_i$$

$$(Ic)\ e_{i1}\in\max\left[a_1+\frac{2^{n-1}\left(k_1\left(e_{it}-e_{jt}\right)\right)^{n-1}}{n}\beta_{i1}(ke_{i1}+\lambda a)-\frac{u}{2\varphi}e_{i1}^2+a_2\right.$$
$$\left.+\frac{2^{n-1}\left(k_2\left(e_{it}-e_{jt}\right)\right)^{n-1}}{n}\beta_{i2}(ke_{i2}+v_i)-\frac{u}{2\varphi}e_{i2}^2\right]$$

F_i is the sum of the two-stage retained utility of the solver i, which is the exogenous constant. By the assumption of homogeneity, there are $e_{11}=e_{21}=\ldots=e_{n1}=e_1$, $\beta_{11}=\beta_{21}=\ldots=\beta_{n1}=\beta_1$. Since θ_1 follows a normal distribution with mean value 0 and variance value $2\left(\lambda^2a_y^2+a_E^2\right)$, there are $k_1(0)=\frac{1}{2}$ and $h_1(0)=\frac{1}{2\sqrt{(\lambda^2a_y^2+a_E^2)\pi}}$. Thus, the equilibrium solution of first task phase is obtained, which is shown in Table 4-1.

Table 4-1 The equilibrium solution of the reputation incentive model

	Task Stage 2 (T=2)	Task Stage 1 (T=1)
e_i^*	$\frac{k<f}{nu}$	$\frac{k<f(1-r)}{nu}$
$\{3_i^*$	$\frac{na_2u}{na_2u+(n-1)(nuv+k^2<f)}$	$\frac{na_1u(r\{3_2^*+(1-r))}{na_1u+(n-1)(nu\lambda a+(1-r)k^2<f)}$
a_i^*	$\frac{n1-\{3_2^*}{n}(ke_2+v)-\frac{u(n1-1)}{2<f}e_2^{*2}$	——
U^*	$(1-1)(\frac{k^2<f}{2nu}+v)$	$\left[\frac{k^2<f(1-r)(1+r)}{2nu}+\lambda a\right]+1\left(\frac{k^2<f}{2nu}+v\right)-L F_i$
$^*_i$	$\frac{1}{n}(\frac{k^2<f}{2nu}+v)$	——

4.4.3 Mechanism Analysis of Reputation Incentive

Based on the expressions of $\{3^*_2$, e^*_2, $\{3^*_1$, e^*_1, this part discusses the mechanism of the two-stage reputation incentive. First, Results 1 and 2 are obtained.[14]

Result 1: (1) When $n > 1$, $\{3^*_2$ is related to v and a^{*2}_2 is related to v. The reputation incentive mechanism affects the deterministic income of the solver in the second task phases by changing unit performance incentive strength $\{3^*_2$; and by adjusting the fixed reward level a^*_2. (2) Reputation output has a negative effect on $\{3^*_2$; when $1 > x(n) = \frac{na_2^2u^2}{(na_2u+(n-1)(nuv+k^2<f))^2}$, reputation output has a positive effect on the fixed reward level; and when $1 < x(n)$, reputation output has a negative effect on fixed reward levels. (3) $x(n)$ is negatively correlated with n.

Discussion: Result 1 shows that the explicit reputation output of the solver (determined by the performance output and reputation expectation value of Stage 1) in Stage 2 will increase the unit performance reward coefficient of the winning solver and have an impact on the fixed reward level of all solvers. The

[14] The proof process of all results in this chapter is presented in Appendix.

higher the explicit reputation output, the lower the unit performance incentive strength from the seeker. It shows that under the condition of asymmetric information, the seeker will utilise the qualification of the solver with high reputation level to reduce the incentive cost. The effect of reputation output on fixed rewards depends largely on the solver’s overall bargaining power:

● When the bargaining power is higher than a certain threshold, the performance of the solver in the first task stage will improve the seeker’s expectation of the solver’s ability. In the second task stage, the fixed bonus set for all solvers will be improved.

● When the bargaining power is lower than a certain threshold, all the results will be the opposite. It is worth noting that the more solvers there are, the higher the overall bargaining power, and the higher the SME seeker’s expectations of the solver’s ability. Therefore, in order to make the reputation incentive mechanism play an active role in SMEs’ CCI, it should not only set a fixed bonus for each solver, but also strive to attract more solvers.

Result 2: (1) e^*_1 is positively related to $\{3^*_1$ and negatively related to $\{3^*_2$; (2) e^*_2 is only positively related to $\{3^*_2$ and not related to $\{3^*_1$.

Discussion: Result 2 indicates that, under the explicit reputation incentive mechanism, the optimal effort level of the solver in the second task stage is only related to the unit performance incentive coefficient of this stage, and the optimal effort level of the first stage is related to the unit performance incentive intensity of both stages. Obviously, the second stage indicates the end of the reputation incentives in this model, so the explicit reputation mechanism does not work. The incentive intensity of the second stage will reduce the level of effort in the first stage. In other words, the reputation incentive will leave a “ratchet” effect (Wang and Li, 2016) which weakens the incentive effect on the solver in the first task phase. From $\frac{ae^*_1}{a\{3_2} = \frac{-<fkra_1}{na_1u-<fk^2(n-1)\{3_1}$, it is known that the absolute value of the ratchet effect is inversely proportional to n, proportional to $<f$, and proportional to $\{3_1$. Therefore, from the perspective of reducing the

ratchet effect of the explicit reputation incentive, it is necessary to attract more solvers to participate.

4.4.4 Sensitivity Analysis

This section analyses the influence of $<f$, r, n and other important parameters on the incentive effect. Results 3 to 6 are obtained.

Result 3: (1) e_2^* is positively related to $<f$, when $n > 1$, $\{3_2^*$ is negatively related to $<f$, when $n = 1$, $\{3_2^*$ is not related to $<f$, (2) e_1^* is positively related to $<f$, when $n > 1$, $\{3_1^*$ is negatively related to $<f$, when $n = 1$, $\{3_1^*$ is not correlated to $<f$.

Discussion: Result 3 reveals the role of implicit reputation in the reputation incentive mechanism of SMEs' CCI. First of all, paying attention to implicit reputation means the decrease of the effort cost of the solver, so it will increase the effort of each solver. Secondly, as long as there are more than two competing solvers, the implicit reputation will reduce the unit performance incentive of the seeker. This shows that the internal friction caused by the competition mechanism among the solvers will reduce the marginal contribution of the implicit reputation, resulting in a decline in the solver's bargaining power, so that the seeker has the opportunity to reduce the cost of performance rewards.

Result 4: (1) e_2^* is not related to r; when $n > 1$, $\{3_2^*$ is positively related to r, and when $n = 1$, $\{3_2^*$ is not related to r; (2) e_1^* is negatively related to r; $\{3_1^*$ is negatively related to r.

Discussion: Since r represents the degree of modification in explicit reputation output based on performance in the previous task stage, and also represents the uncertainty of the reputation output, hence, Result 4 indicates that the seeker's attention to the explicit reputation will weaken the efforts (i.e. the task performance) of the solver in the first stage, but not affect the efforts in the second stage, which confirms Result 2. Result 4 also shows that in the CCI with multiple solvers' participation, although the explicit reputation does not change the solver's effort in the second task stage, it will definitely affect the intensity of the performance reward paid by the seeker at this stage. Also, due to the competition effect among the solvers, the unit performance incentive coefficient β_2^* will increase with the increase of the reputation modification coefficient. This shows that the rise in the reputation modification coefficient means the uncertainty of the solver winning the task in the second phase is increased, which results in the reduction of the solver's effort level. It is also found that β_1^* is negatively related to the explicit reputation modification coefficient, indicating that the greater the uncertainty of explicit reputation, the lower the performance rewards obtained by the solver in the first task phase.

Result 5: e_2^*, β_2^*, e_1^* and β_1^* are all negatively related to n.

Discussion: Result 5 shows that under the reputation incentive mechanism, no matter which task stage it is, the increase in the number of solvers will weaken the performance incentive effect (the optimal effort level of the solver and the unit performance incentive strength of the seeker). This is because in the "winner-takes-all" featured crowdsourcing contest, only the winner can achieve the task performance bonus. Arguably, more solvers mean that the probability of each one winning decreases, resulting in a decrease in the marginal benefit of the effort level, which will reduce the solver's efforts, and the unit performance reward decreases accordingly. Therefore, although the number of solvers is conducive to reducing the reputation ratchet effect and improving the fixed income of each solver, it is not conducive to maximising the incentive effect.

Result 6: (1) U_2^* is not related to r, positively related to φ, and negatively related to n ; (2) U_1^* is negatively related to r , positively related to φ , and negatively related to n.

Discussion: Result 6 elaborates the influence of the reputation incentive mechanism on the benefit of the seeker. Because the final stage's reputation does not need to be modified, the explicit reputation correction coefficient r does not affect the benefit in the second task phase, but will reduce the benefit in the first phase. Therefore, the seeker under the reputation mechanism prefers the solver with a stable reputation. The deterministic benefit of the seeker in the two task phases increases with the increase of the implicit reputation coefficient φ of the solver, and decreases with the increase in the number of solvers. Under the reputation incentive mechanism, the seeker has the motivation to encourage the solvers to increase their efforts to share innovation costs by means of the implicit reputation incentive, and should appropriately reduce the scale of the contest, in order to motivate a single solver to win the performance bonus by improving solution quality.

4.5 Incentive Mechanism without Considering Reputation

When the reputation is not considered, the performance output of the solver is only related to the solver's efforts and random factors, but not related to reputation factors, such as qualification and public praise. The incentive models in the two phases are consistent. The performance output of the solver i can be expressed as:

$$m_i = ke_i + \varepsilon_i,\ i = 1,2,\dots,n \tag{4-17}$$

e_i is the effort level of each solver. Considering that the uncertainty of performance output does not actually change with reputation, $\varepsilon_i \sim N(0, \lambda^2\sigma_r^2 + \sigma_\varepsilon^2)$ is set. Without considering the implicit reputation, it is assumed the effort cost of each solver is $c(e_i) = \frac{\mu}{2}e_i^2$. Referring to Equation (4-6), the probability is that the solver i winning the task is $P(e_i) = \frac{2^{n-1}(\Phi(k(e_i - e_j)))^{n-1}}{n}$. Still considering the seeker offering a fixed bonus α to each solver, and giving the winning solver the unit performance incentive reward β_i as the task bonus. The expected return of the solver i can be expressed as: $w_i = \alpha + P(e_i)\beta_i ke_i$. When reputation is not considered, the optimal incentive problem is determined by α, β_i and e_i. The optimal incentive model can be expressed as:

$$\max_{\alpha, e_i, \beta_i} U = \sum_{i=1}^{n}\left[\frac{2^{n-1}\left(\Phi\left(k\left(e_i - e_j\right)\right)\right)^{n-1}}{n}(1 - \beta_i)ke_i\right] - n\alpha \tag{4-18}$$

$$s.t.\ (IR)\ a + \frac{2^{n-1}(_1\left(k\left(e_i - e_j\right)\right))^{n-1}}{n}\beta_i k e_i - \frac{u}{2}e_i^2 \geq F_0$$

$$(Ic)\ e_{i2} \in \max\left[a + \frac{2^{n-1}(_1\left(k\left(e_i - e_j\right)\right))^{n-1}}{n}\beta_i k e_i - \frac{u}{2}e_i^2\right]$$

Similar to the solution process in Section 4.4.2, and taking full consideration of the symmetry of the model, the expression of the optimal effort input level e_0 of each solver and optimal unit performance incentive strength β_0 of the seeker is:

$$\beta_0^* = \frac{na_1u}{na_1u + (n-1)k^2},\ e_0^* = \frac{k}{nu} \tag{4-19}$$

4.6 Value Analysis of the Reputation Incentive Mechanism

This section provides a detailed comparison of the optimal effort level of the solver and the optimal unit performance incentive level of the seeker with or without the reputation factor, thereby revealing the value of the incentive effect of the reputation mechanism. Results 7 and 8 are obtained.

Result 7: (1) $\beta_0^* > \beta_2^*$ and $\beta_0^* - \beta_2^*$ are both negatively correlated with n; (2) $e_0^* < e_2^*$ and $e_2^* - e_0^*$ are negatively correlated with n.

Discussion: Result 7 shows that the optimal effort level of the solver in the second task stage under the reputation incentive mechanism is higher, while the unit performance incentive coefficient of the seeker is lower than that without the reputation incentive mechanism. The explicit and implicit reputation of the solver helps reduce the incentive cost of the seeker, and the seeker has an intrinsic motivation to implement the reputation incentive mechanism in this stage. In addition, with the increase in the number of solvers, the effect of the reputation mechanism on the increasing of effort level and reduction of the incentive cost will all be weakened. Interestingly, the volume of the task will reduce the value of the reputation incentive mechanism in Stage 2.

Result 8: (1) When $\varphi(1-r) > 1$, $e_1^* > e_0^*$; otherwise, $e_1^* < e_0^*$; (2) When $\beta_2 < \frac{na_1ur+(n-1)(k^2(1-r)\varphi(1+nu\lambda a)}{(na_1u+(n-1)k^2)r}$, $\beta_1^* > \beta_0^*$; otherwise, $\beta_1^* < \beta_0^*$.

Discussion: Result 8 shows under the combined effect of implicit reputation, explicit reputation and contest among solvers, the value of the reputation incentive mechanism in the first task stage has great uncertainty.

In view of the complexity of the boundary conditions, the numerical simulation method is used to verify the influence of the implicit reputation coefficient <f, the explicit reputation correction coefficient r and the number of solvers n on the value of reputation incentive mechanism in the first task stage. Without loss of generality, the following are set: the effort performance coefficient $k = 100$, effort cost coefficient $u = 80$, explicit reputation expectation $a = 0$, explicit reputation performance coefficient $\lambda = 1$, and random variance $a_E^2 = 25$. The relationship between e_1^* and e_0^* is analysed, and the relationship between $\{3_1^*$ and $\{3_0^*$ determined by <f and r. Consequently, the influence of n on $e_1^* - e_0^*$ and $\{3_1^* - \{3_0^*$ is further explored. The results are shown in Figure 4- 2 to Figure 4- 5.

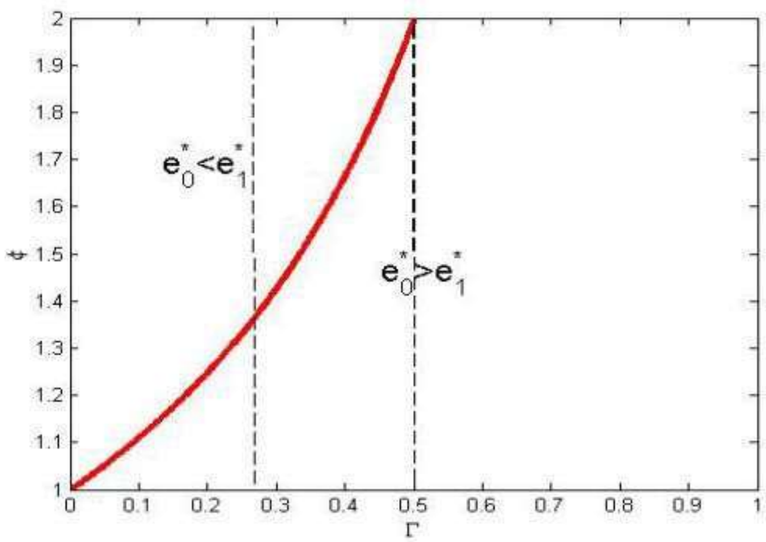

Figure 4- 2 The effect of <p, T on the relationship between e_1^* and e_0^*

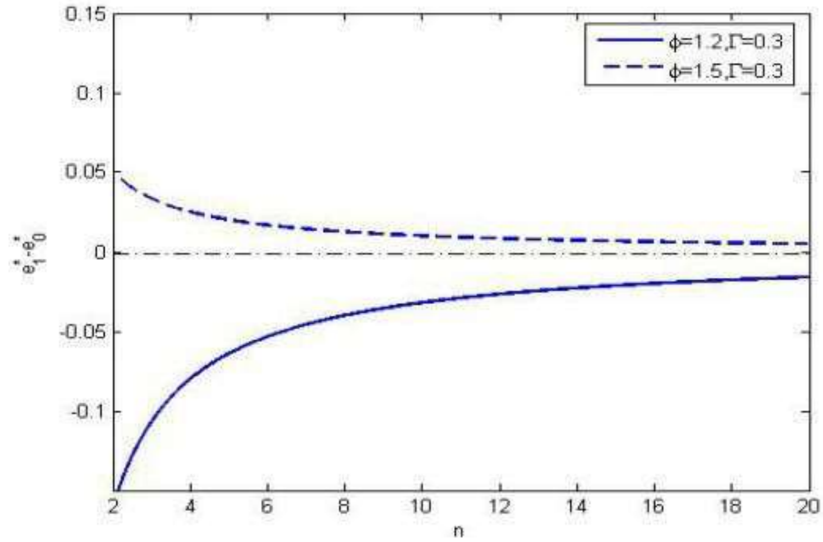

Figure 4- 3 The effect of n on $e_1^* - e_0^*$

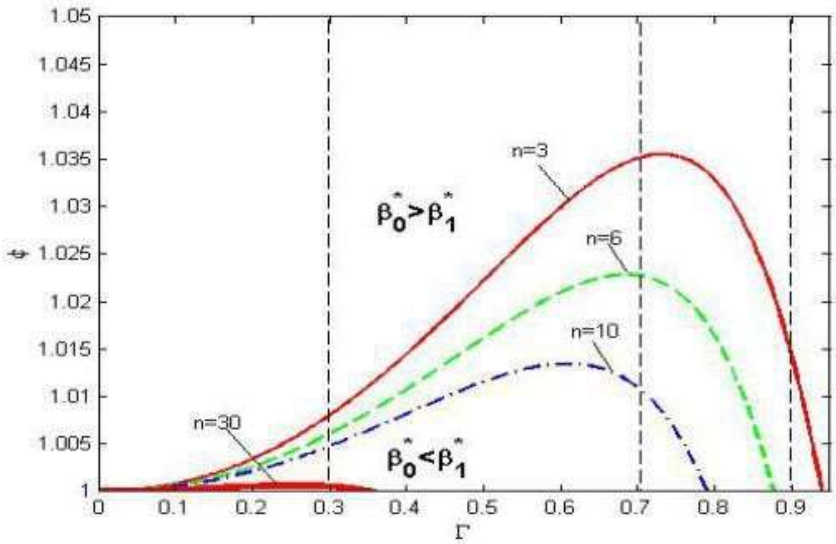

Figure 4- 4 The effect of $<p, T$ on the relationship between P_1^* and P_0^*

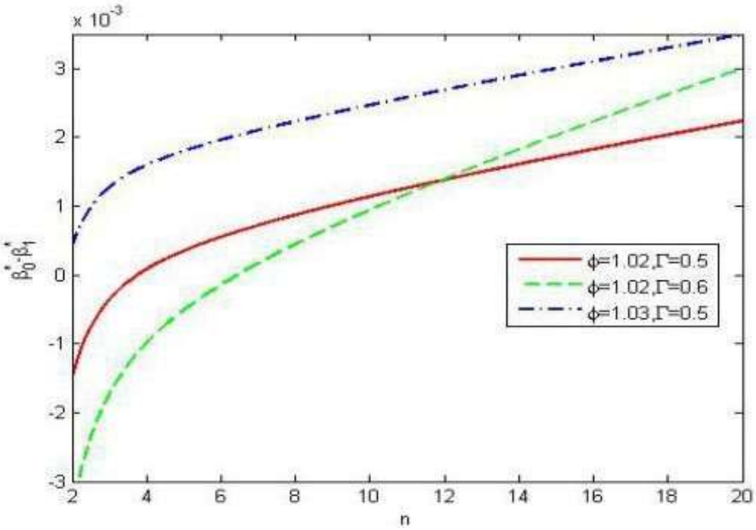

Figure 4-5 The effect of n on $P_0^* - P_1^*$

In Figure 4-2, there is a boundary line of $e_1^* = e_0^*$. This boundary line is a concave curve to the upper right and ends at $r = 0.5$. The upper left of the boundary line is the $e_1^* > e_0^*$ area, and the lower right is the $e_1^* < e_0^*$ area. Intuitively, in the feasible area, reputation incentives have only a low probability of improving the optimal effort level of Stage 1. Specifically, when the explicit reputation uncertainty is $r > 0.5$, there is no Pareto region with $e_1^* > e_0^*$, and the reputation incentive mechanism is worthless in the first task stage; when $r < 0.5$, whether it produces positive value in the first stage also depends on the implicit reputation coefficient $<f$. When $<f$ is higher than the threshold determined by r, the reputation incentive mechanism can simultaneously increase the effort of each solver in the two task phases to achieve *Pareto improvement* (Brendan, 2016). Otherwise the result is opposite. It is worth noting that with the increase of r, the area of $e_1^* > e_0^*$ continues to shrink. If the solver wants to improve the task performance of the first task phase by implementing reputation incentives, the solver needs to improve the implicit reputation and reduce the uncertainty of the explicit reputation. As shown in Figure 4-3, the number of solvers can adjust the size of $e_1^* - e_0^*$, that is, $/e_1^* - e_0^*/$ will decrease with the increase of n due to the existence of the contest mechanism among solvers. So, the expansion of the crowdsourcing scale will lead to a decline in the winning probability of each solver, which will weaken the performance effect of reputation incentives.

Figure 4- 4 and Figure 4- 5 show the influence of the reputation incentive mechanism in the first task stage on the intensity of performance incentive set by the seeker, which is the sign of the solver's economic benefit. The boundary of $\beta_1^* = \beta_0^*$ first increases and then decreases with the increase of r, but it is always below $\varphi = 1.04$. As n increases, the overall height of the boundary continuously decreases, and even when $n > 30$, the entire feasible area satisfies $\beta_1^* < \beta_0^*$. This shows that in most cases, out of the seeker's consideration of the future benefit, the unit performance reward gained by the solver in the first task stage under the reputation incentive mechanism will be lower than that without the reputation incentive mechanism. Consequently, the opposite can only happen if the following two conditions are met at the same time: (1) the number of solvers is small; (2) the implicit reputation factor is very small (below 1.04). At the same time, the probability of meeting these two conditions rises first and then decreases with the increase of explicit reputation uncertainty. Figure 4- 5 shows that $\beta_0^* - \beta_1^*$ increases unilaterally as n increases, indicating that the increase in the number of solvers will further deepen the negative economic value of solvers produced by the reputation incentive mechanism. This indirectly confirms Result 5.

4.7 Research Limitations and Reflection

4.7.1 Research Limitations

● Because the complexity of the reputation incentive model is high, the risk preference of both the seeker and solver is not considered.

● Solvers are assumed to be homogeneous, hence, their heterogeneity of problem-solving ability and innovation level is ignored.

● The reputation incentive model is only applicable to professional tasks of SMEs CCI, it is not suitable for creative tasks. This is because according to Tian (2016), the performance function and the winning probability show a significant difference between professional and creative crowdsourcing contest tasks. And professional tasks are exclusive to experienced solvers. The experience that a solver has is represented by solver's rankings and points which are the explicit reputation on the platform.

4.7.2 Reflection

In response to the questions posed in the Introduction:

<u>Question (1):</u> How to integrate explicit and implicit reputation into the design process of the incentive mechanism?

By taking the observable performance of the previous stage as the explicit reputation and adjusting the expected performance of the later stage, the designer can implement a linear performance incentive mechanism based on the expected performance of all subsequent stages. In addition, the designer can share a part of the solvers' innovation cost according to the reputation level of solvers, so as to integrate the implicit reputation into the incentive mechanism.

<u>Question (2):</u> How does this dual reputation mechanism affect the innovation efforts made by solvers and the incentive reward paid by seekers in each task stage? Will the task performance and economic benefit of each task stage be really improved?

The reputation incentive mechanism will certainly improve the innovation efforts made by solvers and the incentive reward paid by seekers, result in higher performance and economic of both sides in Stage 2. However, the result of Stage 1 is likely to be different due to the ratchet effect.

<u>Question (3):</u> What impact will the size and uncertainty of reputation, as well as the number of solvers, have on the incentive effect of the reputation mechanism?

The uncertainty of the explicit reputation, as well as the number of solvers, will reduce the advantages of reputation incentive mechanism in improving innovation efforts and crowdsourcing performance.

4.8 Conclusions

This chapter studies the reputation incentive mechanism of SMEs' CCI, and the process is shown in Figure 4-1. It is assumed that the solver's winning probability depends on the sum of its efforts and explicit reputational performance, and the seeker can correct the solver's reputation based on the solver's observed performance of the first task stage during the second task stage. The performance incentive model with dual reputation is then solved through two consecutive task stages and compared with the incentive mechanism without reputation. The result shows that the reputation incentive mechanism can affect the solver's economic benefit of Stage 2 through the unit performance incentive reward and the fixed reward, and it can have a ratchet effect on the solver's effort in the first stage. The best way to reduce the rachet effect is to increase the number of solvers. The implicit reputation will increase the solvers' effort in each stage, and the uncertainty of the explicit reputation will reduce the effort and task performance in both task stages. Interestingly, only when the explicit reputation uncertainty is lower and the implicit reputation coefficient is higher than a threshold, will the incentive effect be higher than the no reputation incentive model in both task stages.

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5 KNOWLEDGE SHARING INCENTIVE MECHANISM OF SMES CROWDSOURCING CONTEST INNOVATION CONSIDERING FAIRNESS CONCERN

Abstract

Knowledge-sharing behaviour in the crowdsourcing community is an emerging area of interest for decision makers and academic scholars operating in the field of innovation, design-thinking, and strategic project management. If knowledge-sharing behaviours are understood and implemented correctly by project managers, it can be extremely useful for SMEs to reduce the cost of associated with innovation project management efforts, whilst improving task performance and affect fairness concern of solvers (i.e. crowdsourcees who offer services to solve crowdsourcing problems). In this chapter, the importance of stimulating solvers' knowledge-sharing behaviour in SMEs' when undertaking crowdsourcing contest innovation (CCI) tasks is challenged and reviewed. The models with and without knowledge-sharing incentives (called KS model and NKS model, respectively) are built and the impact of fairness concerns' sensitivity on the effect of incentive mechanisms analysed. Finally, a comparison is made between the KS model and NKS model.

Interestingly, the results show that knowledge-sharing behaviour can improve crowdsourcing performance, but cannot improve the solvers' winning probability in SMEs' CCI. In the KS model, the knowledge-sharing effort is negatively related to solvers' fairness concern, but the private solution effort is positively related to it. The relationship among the CCI task performances, the absolute economic benefits of solvers and fairness concerns remains uncertain. It is also found that the KS model can achieve a win-win result for economic benefits of both the seekers (i.e. SMEs or crowdsourcers who issue the crowdsourcing tasks) and solvers, while economic value grows with the increase of the solvers' sensitivity to fairness concern. From the results, it is suggested that a knowledge-sharing community, coupled with a reasonable sharing behaviour evaluation system, should be established on crowdsourcing platforms.

Furthermore, seekers should treat solvers’ fairness concern carefully, and better transform it into “pride” rather than “jealousy”.

Keywords: fairness concern; knowledge-sharing incentive mechanism; crowdsourcing community

5.1 Introduction

The open and unconstrained nature of the Internet provides a better opportunity for knowledge dissemination and sharing (Yao, Gao and Ouyang, 2014; Shi, Lin and Tang, 2015). Through knowledge-sharing between the seekers and solvers, and among the solvers, the professional skills and knowledge level of the solvers can be improved, the solution time can be shortened, and innovation costs can be saved, so that SMEs can obtain high-quality solutions in a timely and effective manner. Therefore, knowledge-sharing is not only an importantnon-material motivation for the solvers in SMEs crowdsourcing contest innovation, but also caters to the needs of SMEs' innovation. In fact, some companies have begun to create a new ecological civilisation - a virtual crowdsourcing community (referred to as: crowdsourcing community). Difficult innovation problems are released to the public via the Internet, and through diversified knowledge-sharing among the public, R&D risks of enterprises can be avoided, and brand loyalty can be enhanced (Shan, Jiang and Yang, 2017). For example, the core code of the Linux system is developed by programmers, scattered all over the world, through the open source community and is open to the public (Olson and Rosacker, 2012). World-renowned companies, such as P&G (Ozkan, 2015) and Amazon (Schmidt and Jettinghoff, 2016), have established crowdsourcing communities to encourage employees and the public to share knowledge. Members of the crowdsourcing community can break through the limitation of time and space, exchange knowledge freely and share information with other members, learn professional knowledge and gain unique viewpoints, make tacit knowledge explicit and individual knowledge public and, at last, realise the goal of community knowledge value co-creation.

However, creating a crowdsourcing community of SMEs CCI still faces great difficulties, the root cause of which is that the solver cannot avoid the complete competitive relationship brought about by the "winner-takes-all" rule. Additionally, the horizontal fairness concern of other solvers' "free-riding" (Grossman and Hart, 1980) behaviour is also an important factor hindering the knowledge-sharing of the solver (Shan, Jiang and Yang, 2017). Fairness concern is a psychological feature commonly found in human beings (Zhang and Wang, 2018). It can cause people to be highly self-interested and make them pay more attention to the rationality of interest distribution between themselves and others under the constraints of project resources and time cost. Therefore, in the process of knowledge-sharing, people will carefully consider the benefits they obtain and the distribution results to maximise their personal utility (Zhang and Zhang, 2011). Undoubtedly, the fairness concern of solvers will seriously affect their knowledge-sharing behaviour in the crowdsourcing community, which in turn will affect their own skills, change the performance of SMEs' CCI and the economic benefits of both the seekers and solvers.

Research related to knowledge-sharing and its incentive mechanism is abundant. In terms of knowledge-sharing motives, many scholars have found that the motivations for individuals to share knowledge are non-material subjective factors, such as personal expectations, trust, and emotions (McMillan and Chavis, 1986; Davenport and Prusak, 1998; Hsu *et al.*, 2007; Zhang, 2009). Some researchers believe that material incentives are more conducive to the knowledge-sharing behaviour in the crowdsourcing community (Shi, 2010). Research by Blohm *et al.* (2010) on IT creative projects using wiki technology found that collaboration enhances idea quality; it is the most helpful for forming knowledge-sharing behaviour and improving the quality of solutions. Hao, Hou and Zheng (2016) followed this idea and established the Nash game model among the solvers, and the Stackelberg game model between the seekers and solvers, and interpreted the impact of various factors on the performance of knowledge-sharing in the crowdsourcing community from the models' results. Shan, Jiang and Yang (2017) empirically studied the correlation between relational embedding and knowledge-sharing behaviour through the data of Xiaomi BBS (bbs.xiaomi.cn) and the Zbj.com crowdsourcing community (quan.zbj.com/forum.php). Besides, studies about fairness concern mainly focus on the problems in the areas of supply chain and employee motivation. Caliskan-Demirag, Chen and Li (2010) qualitatively described the characteristics of supply chain parties' fairness concern utility function. Guan, Ye and Yin (2020) studied a supply chain coordination problem with an upstream manufacturer and a downstream retailer that have Nash bargaining fairness concerns. Du *et al.* (2010) quantified the functional form of fairness concern utility, pointing out that fairness concern utility is closely related to the income gap between an individual and its reference subject, and discussed the influence of a member's fairness concern on the performance and coordination mechanism of the supply chain.

It can be seen that the existing literature on the knowledge-sharing incentive mechanism in SMEs' CCI is very rare with regard to the certain contradiction between competition and knowledge-sharing itself. Moreover, the relationship between solvers' fairness concern and the effect of knowledge-sharing incentive mechanisms remains unclear. In view of the important role of knowledge-sharing on innovation, can the knowledge-sharing behaviour of the solvers improve their winning probability in CCI that is characterised by "winner-takes-all"? If not, what incentive mechanism should the taken by organisers in the crowdsourcing community to stimulate the knowledge-sharing behaviour of the solvers? How is the value of the knowledge-sharing incentive mechanism, mentioned above on crowdsourcing performance and the economic benefits of both the seekers and solvers, affected by the psychology of fairness concern? The solution to these problems is of great significance to maximise crowdsourcing performance.

So, taking the characteristics of both collaboration and competition among solvers in SMEs' CCI fully into consideration, a knowledge-sharing incentive mechanism model is built under the "winner-takes-all" reward rule. Also, the impact of the fairness concern sensitivity on the optimal level of the solvers' private effort, knowledge-sharing level, and optimal knowledge-sharing incentive intensity are analysed and discussed, which reveal how fairness concern and knowledge-sharing affect the performance of crowdsourcing tasks and the economic benefits of the seekers.

5.2 Problem Description and Important Assumptions

This considers a CCI task composed of only one SME as the seeker, a crowdsourcing platform, and $n\ (n \geq 2)$ homogeneous solvers (participants). In order to acquire external knowledge and improve professional skills to reduce the effort cost, the solver is eager to share knowledge. Therefore, a knowledge exchange and sharing area is established on the platform, referred to as a crowdsourcing community. The organisation of the CCI task still follows the general process: the seeker evaluates the solution submitted by solvers, determines the winning solver (aka the winner) according to its performance (quality) level, and a fixed task award of amount A goes to the winner. Due to the existence of the crowdsourcing community, the efforts of the solver i $(i = 1,2, \ldots, n)$ can be divided into two parts: private effort e_i and knowledge-sharing effort s_i. Private effort can directly improve the solution performance of the solver, while knowledge-sharing effort can help to improve the knowledge stock level in the whole crowdsourcing community, indirectly improving the knowledge and skills level of all solvers and, at the same time, help to improve the performance of the task and reduce the solution cost.

According to the research of Hao, Hou and Zheng (2016), the private effort cost is set as $c(e_i) = c_e e_i$, which is a linear function of private effort. The relationship between private effort and the task performance submitted can be described as: $r(e_i) = \eta \ln e_i$, which indicates that the private effort can improve the task performance; however, the increase in increments continues to decrease as the effort level increases, where η is called the private effort performance conversion rate. The knowledge-sharing behaviour in the community causes a change in the stock of shared knowledge. According to Zhang and Zhang (2011), the shared knowledge stock of the crowdsourcing community can be set as $S = \prod_{j=1}^{n} s_j^{a}, (0 < a < 1)$, where a is the proportion of knowledge input of each solver. Obviously, when the solvers are homogeneous, the result is: $a = \frac{1}{n}$. Further, referring to the studies of Blohm *et al.* (2010) and Yao, Gao and Ouyang (2014), setting the task performance increased by the shared knowledge stock is $\beta_i \prod_{j=1}^{n} s_j^{\frac{1}{n}}$ and the reduced private effort cost is $c_e k_i \prod_{j=1}^{n} s_j^{\frac{1}{n}}$. β_i $(0 < \beta_i < 1)$ is the shared knowledge performance conversion rate, and k_i $(0 < k_i < 1)$ is the knowledge-sharing private cost reduction rate, which respectively represent the extent to which shared knowledge improves crowdsourcing task performance and reduces the cost of private effort. The cost of the knowledge-sharing effort paid by the solver i is $\frac{1}{2}hs_i^2$.

By assuming all solvers in the crowdsourcing community have fairness concern, and according to the studies by Du *et al.* (2010) and Gao and Nie (2014), the utility function of the solver under fairness concern can be expressed as:

$$U_i = \pi_i + \lambda_i \sum_{j=1, j\neq i}^{n} (\pi_i - \pi_j) \tag{5-1}$$

π_i is the expected return of the solver i; λ_i $(0 < \lambda < 1)$ is the fairness concern coefficient, representing the sensitivity of the solver i to the fairness in returns. Equation (5- 1) indicates that the solver is concerned not only with the absolute size of its own expected revenue, but also with the relative value of all other solvers' expected returns. Other important assumptions used in this chapter are:

(1) All solvers are homogeneous, with the same knowledge-sharing performance conversion rate, the same knowledge-sharing solution cost reduction rate and the same fairness concern coefficient. That is $\beta_1 = \beta_2 = \ldots = \beta_n = \beta$, $k_1 = k_2 = \ldots = k_n = k$ and $\lambda_1 = \lambda_2 = \ldots = \lambda_n = \lambda$; and all solvers are risk neutral.

(2) The expected performance of the winning solver is the expected performance of the crowdsourcing task, and the revenue conversion rate of the expected performance is 1.

(3) In the model of the knowledge-sharing incentive mechanism, the seeker is the leader and the solver is the follower. It is a static game among the solvers.

According to the above description and assumptions, the performance level of the solution provided by the solver can be expressed as:

$$v_i(e_i, s_i, \varepsilon_i) = \eta \ln e_i + \beta_i \prod_{j=1}^{n} s_j^{\frac{1}{n}} + \varepsilon_i \tag{5-2}$$

ε_i is a random term, obeying a Gumbel distribution (Nadarajah and Kotz, 2004) with mode 0 and scale parameter u (Hao, Hou and Zheng, 2016). It can be deduced that the probability of the solver i winning the task is:

$$
\begin{aligned}
P\Big(v_i(e_i, s_i, \varepsilon_i) > \max\big(v_j(e_j, s_j, \varepsilon_j)\big)\Big) &= \frac{\exp\left(\lambda \ln e_i + \beta \prod_{j=1}^{n} s_j^{\frac{1}{n}}\right)}{\sum_{j=1}^{n} \exp\left(\lambda \ln e_j + \beta \prod_{j=1}^{n} s_j^{\frac{1}{n}}\right)} \\
&= \frac{1}{1 + (n-1)\exp\left(\frac{\lambda(\ln e - \ln e_i)}{u}\right)}
\end{aligned}
\tag{5-3}
$$

In the final expression of Equation (5-3), $\prod_{j=1}^{n} s_j^{\frac{1}{n}}$ does not exist. It means that, under the condition of $\beta_1 = \beta_2 = \ldots = \beta_n = \beta$, although knowledge-sharing is conducive to improving the task performance level, all solvers will benefit from this. Therefore, knowledge-sharing will not directly increase the solver's probability of winning the task. The expected net income of the seeker (i.e. the difference between the performance of the winning solution and the incentive cost) is obtained:

$$
V = \sum_{i=1}^{n} \frac{\lambda \ln e_i + \beta_i \prod_{j=1}^{n} s_j^{\frac{1}{n}}}{1 + (n-1)\exp\left(\frac{\lambda(\ln e - \ln e_i)}{u}\right)} - A - F(s_k)
\tag{5-4}
$$

The first term in Equation (5-4) is the expected performance of the task, which is the total revenue of the seeker. It is expressed as the weighted sum of the winning probability of each solver and its performance. The second term is the fixed reward paid by the seeker to the winner. The third term is the knowledge-sharing rewards paid by the seeker, which is 0 when the knowledge-sharing incentive is not implemented.

5.3 Methods

Considering the fairness concern of the solver, the principal-agent theory and game theory are used to construct the knowledge-sharing incentive mechanism model in the crowdsourcing community of SMEs CCI. According to the results of the model, the value of the knowledge-sharing incentive mechanism and its influencing factors are discussed. Specific steps are as follows:

Step 1: Determining the performance output expression of the solver in the knowledge-sharing community. The solver's performance output consists of two parts: (1) the performance output of private effort; (2) the performance output of knowledge-sharing effort.

Step 2: Calculating the winning probability of the solver in the crowdsourcing community. The winning probability is based on the performance output, which is expressed as the probability that the performance output of the winning solver is higher than the performance output of all other solvers.

Step 3: Constructing the objective functions of the seeker and the solver without the knowledge-sharing incentive and solving the model. Because the model with knowledge-sharing incentive is the main focus of this chapter, the details are not described here. Compared with Steps 4 to 5, in this model, there is no knowledge-sharing incentive expenditure in the incentive cost of the seeker, and there is no knowledge-sharing benefit in the total income of the solver. The rest are similar to Steps 4 to 5.

Step 4: Constructing the objective functions of the seeker and the solver with the knowledge-sharing incentive. The goal of the seeker is to maximise the expected net income (the difference between the expected total income and the incentive cost). The expected total return is expressed as the weighted average sum of the performance output of the winning solver with the winning probability as the weight, and the incentive cost is the sum of the task reward expenditure and the knowledge-sharing incentive expenditure. The goal of the solver with fairness concern is utility maximisation. The utility of the solver is determined by its net income (the difference between the total income and the effort cost), and the net income of other solvers and the fairness concern coefficient. The total income of the solver is divided into two parts: expected task reward income (the product of the fixed task reward and winning probability) and knowledge-sharing income. The effort cost is the sum of private effort cost and knowledge-sharing effort cost.

Step 5: Model solving. Specific steps are:

(5.1) Determining the decision variables of the seeker and the solver: the decision-making variables of the seeker are the task reward A and the unit knowledge-sharing incentive amount b . The decision variables of the solvers are the private effort level e and the knowledge-sharing effort level s.

(5.2) Determining the game sequence of the two parties: the seeker is the leader, and the solver is the follower.

(5.3) According to the inverse solution method, first solve the decision of the solver. The expressions of e and s are obtained by using the first partial derivative methods.

(5.4) Solving the decision of the seeker: substituting the expressions of e and s into the seeker's objective function to obtain the expressions A and b, and then using the first-order partial derivative method to obtain the specific expressions of A and b.

(5.5) Substituting the expressions of A and b back to the intermediate results of the above steps to obtain all the decision variables in the model, the performance of the crowdsourcing task, and the specific forms of the economic benefits of both parties.

Step 6: Analysis of the model results. According to the expressions of various decision variables, crowdsourcing performance and economic benefits, by adopting the sensitivity analysis method (sign of the first-order partial derivative), the key indicators of the solver's private effort, the solver's knowledge-sharing level, the unit knowledge-sharing reward, the performance of the crowdsourcing task, and the economic benefits of both parties are analysed respectively. In particular, the impact of the fairness concern coefficient (λ) is deeply explored. The difference method is used to compare and analyse the performances and economic incomes under the models with or without knowledge-sharing incentive. Lastly, the value of the knowledge-sharing incentive mechanism is summarised.

Step 7: Numerical simulation. If the expressions of some variables are too complicated to be directly analysed by sensitivity analysis or the difference method, numerical examples and computer simulation methods are used to obtain more intuitive results.

Step 8: According to the analysis of the model results, disseminating some management implications.

5.4 Model Construction and Solution

5.4.1 Non-knowledge-sharing Incentive Model (NKS)

In order to compare with the knowledge-sharing incentive mechanism, this part first studies the model when the knowledge-sharing incentive is not implemented in the crowdsourcing community. Without considering the fixed rewards of all solvers, the solver's behaviour is determined by incentive compatibility (a mechanism showing if it is best for all participants to be truthful in their action) (Reichelstein, 1984; Ehlers *et al.*, 2020). From the above description, when there is no knowledge-sharing incentive, the expected net return of the risk-neutral solver i can be expressed by the difference between the task reward when it wins the task and the two types of effort costs:

$$\pi_i = \frac{A}{1 + (n-1)\exp\left(\frac{1(\ln e - \ln e_i)}{u}\right)} - c_e\left(e_i - k\sum_{j=1}^{n}\frac{1}{n}s_j\right) - \frac{1}{2}hs_i^2 \tag{5-5}$$

From Equation (5-1), when fairness concern exists, the target utility function (objective function) of the solver i is:

$$
\begin{aligned}
U_i = & \frac{((n-1)\lambda + 1)A}{1 + (n-1)\exp\left(\frac{1(\ln e - \ln e_i)}{u}\right)} + \left((n-1)\lambda + 1\right)\Big(\\
& - c_e\left(e_i - k \prod_{j=1}^{n} s_j^{\frac{1}{n}}\right) - \frac{1}{2}hs_i^2\Big) \\
& - \lambda \sum_{m=1, m\neq i}^{n} \left[\frac{A}{1 + (n-1)\exp\left(\frac{1(\ln e - \ln e_m)}{u}\right)} \right. \\
& \left. - c_e\left(e_m - k \prod_{j=1}^{n} s_j^{\frac{1}{n}}\right) - \frac{1}{2}hs_m^2\right]
\end{aligned}
\qquad \textbf{(5-6)}
$$

In order to get the balanced private effort and knowledge-sharing level, find the first-order partial derivatives of U_i with respective to e_i and s_i, and substitute the symmetric strategies $e = e_i = e^*$ and $s = s_i = s^*$ caused by the homogeneity hypothesis into the above derivatives. Following the method of Step 5， the equilibrium solution of NKS model is obtained and is shown in Table 5-1.

Table 5-1 The equilibrium solution of NKS model and KS model

	NKS model	KS model
e_i^*	$\frac{A(n-1)1(n\lambda+1)}{uc_e n^2((n-1)\lambda+1)}$	$\frac{A(n-1)1(n\lambda+1)}{uc_e n^2((n-1)\lambda+1)}$
s_i^*	$\frac{kc_e}{((n-1)\lambda+1)nh}$	$\frac{((n-1)\lambda+1)\{3+kc_e}{2((n-1)\lambda+1)nh}$
b_i^*	——	$\frac{((n-1)\lambda+1)\{3-kc_e}{2n((n-1)\lambda+1)e}$
$E(v^*)$	$1\ln\left[\frac{A(n-1)1(n\lambda+1)}{uc_e n^2((n-1)\lambda+1)}\right] + \frac{\{3kc_e}{((n-1)\lambda+1)nh}$	$1\ln\left[\frac{A(n-1)1(n\lambda+1)}{uc_e n^2((n-1)\lambda+1)}\right] + \frac{(((n-1)\lambda+1)\{3+kc_e)\{3}{2((n-1)\lambda+1)nh}$
π_i	$\frac{k^2c_e^2(2n((n-1)\lambda+1)-1)}{2n^2h((n-1)\lambda+1)^2} + \frac{A}{n}\left[1 - \frac{(n\lambda+1)(n-1)1}{((n-1)\lambda+1)nu}\right]$	$\frac{((n-1)\lambda+1)\{3+kc_e)((n-1)\lambda+1)\{3+(4n((n-1)\lambda+4n-3)kc_e)}{8n^2h((n-1)\lambda+1)^2} + \frac{A}{n}\left[1 - \frac{(n\lambda+1)(n-1)1}{((n-1)\lambda+1)nu}\right]$
	$1\ln\left[\frac{A(n-1)1(n\lambda+1)}{uc_e n^2((n-1)\lambda+1)}\right] + \frac{\{3kc_e}{n((n-1)\lambda+1)nh} - A($	$1\ln\left[\frac{A(n-1)1(n\lambda+1)}{uc_e n^2((n-1)\lambda+1)}\right] + \frac{(((n-1)\lambda+1)\{3+kc_e)^2}{4nh((n-1)\lambda+1)^2} - A$

5.4.2 Knowledge-sharing Incentive Model (KS)

This section considers the model when the knowledge-sharing incentive is implemented in the crowdsourcing community. The designed incentive mechanism is as follows: the seeker makes a reasonable evaluation of the degree of knowledge-sharing by solvers in the crowdsourcing community, and rewards the knowledge-sharing behaviour at unit level b, so that the solver i can obtain the knowledge-sharing benefit of which the amount be_is_i. e_i $(0 < e_i < 1)$ is the knowledge-sharing frequency observed by the seeker, and is used as the basis for evaluating the degree of knowledge-sharing. This frequency can be expressed by observing the communication frequency of the solver in the community and the correlation with the communication content (Hao, Hou and Zheng, 2016). By the assumption of homogeneity, setting $e_1 = e_2 = . . . = e_n = e$. Based on the above description, the process of the knowledge-sharing incentive mechanism in this section is shown in Figure 5-1.

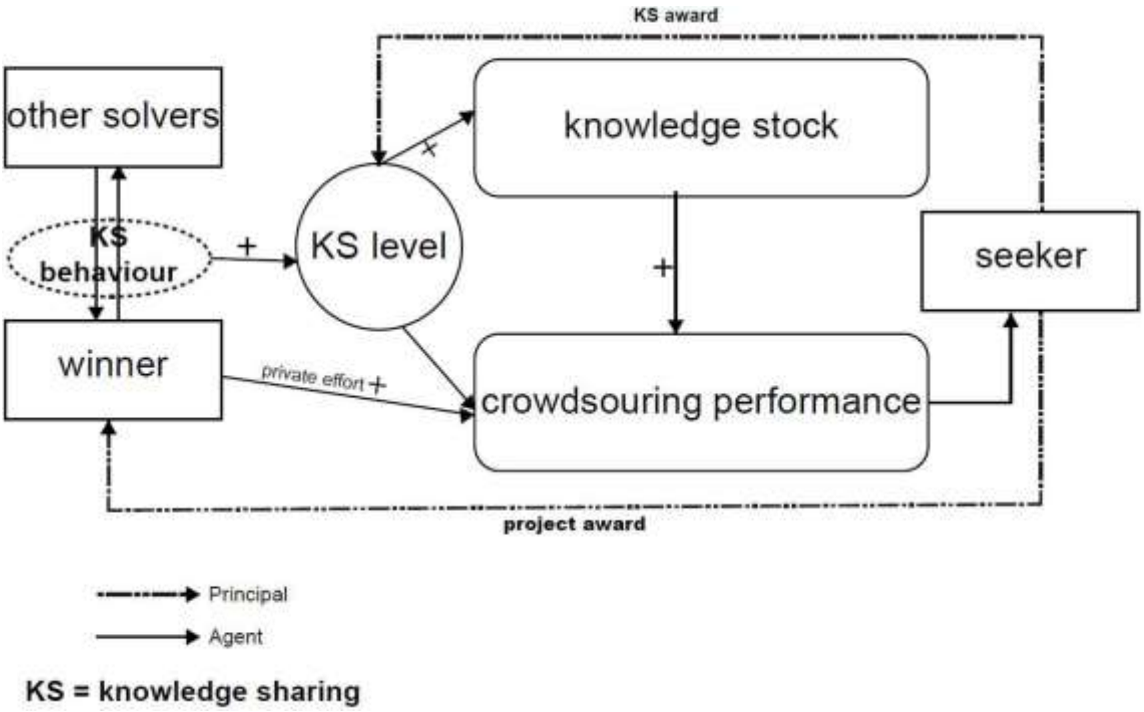

Figure 5-1 Flowchart of knowledge sharing incentive mechanism

(designed by the author)

In the above process, since the knowledge-sharing linear incentive degree b will not only affect the cost of the seeker, but also change the performance of the solver's solution, there is a game relationship between them. The game sequence is: (1) the seeker determines the amount of b ; (2) the solver determines the private effort e_i and knowledge-sharing effort s_i . When the seeker implements the knowledge-sharing incentive, the expected benefit for the solver i can be expressed as:

$$\pi_i = \frac{A}{1 + (n-1)\exp\left(\frac{1(\ln e - \ln e_i)}{u}\right)} + b e s_i - c_e\left(e_i - k \prod_{j=1}^{n} s_j^{\frac{1}{n}}\right) - \frac{1}{2} h s_i^2 \tag{5-7}$$

Compared with Equation (5- 5), Equation (5- 7) has a new term $b0s_i$, which is the expected benefit of the knowledge-sharing. The target utility function (objective function) of the solver i under the incentive of knowledge-sharing regarding Equation (5-1) is:

$$\begin{aligned} U_i = {} & \frac{((n-1)\lambda + 1)A}{1 + (n-1)\exp\left(\frac{1(\ln e - \ln e_i)}{u}\right)} + ((n-1)\lambda + 1)\Big(b e s_i \\ & - c_e\left(e_i - k \prod_{j=1}^{n} s_j^{\frac{1}{n}}\right) - \frac{1}{2}\lambda s_i^2\Big) \\ & - \lambda \sum_{m=1, m\neq i}^{n} \Bigg[\frac{A}{1 + (n-1)\exp\left(\frac{1(\ln e - \ln e_m)}{u}\right)} + b e s_m \\ & - c_e\left(e_m - k \prod_{j=1}^{n} s_j^{\frac{1}{n}}\right) - \frac{1}{2}\lambda s_m^2\Bigg] \end{aligned} \tag{5-8}$$

The expected return of the seeker is still expressed as Equation (5- 4). Following the method of Step 5 ， the equilibrium solution of KS model is obtained, which is shown in Table 5-1.

5.5 Results Analysis

Result 1: The KS model can be established if and only if $\beta > \delta_0(\lambda)$ and $\delta_0(\lambda)$ is negatively correlated with λ.[15]

Discussion: Result 1 indicates that whether the seeker has the incentive to implement the knowledge-sharing incentive depends on the size of the knowledge-sharing performance conversion rate, which represents the extent to which shared knowledge is transformed into task performance. Only when the rate is higher than a certain threshold is the knowledge-sharing incentive feasible; otherwise, the seeker will give up due to the relatively higher cost. In addition, the threshold is negatively related to the fairness concern sensitivity, that is to say, the more the solver cares about fairness, the higher the probability of the seeker implementing knowledge-sharing incentives.

Result 2: The optimal knowledge-sharing linear incentive degree b^* is positively correlated with λ, positively correlated with β, negatively correlated with k, negatively correlated with e, and negatively correlated with n.

Discussion: Result 2 summarises the influencing factors and direction of the optimal knowledge-sharing incentive degree of the seeker when the knowledge-sharing incentive mechanism is established.

First, the optimal knowledge-sharing incentive degree is positively related to the solver's fairness concern. As mentioned in the background to this chapter, those with strong fairness concern are less willing to share knowledge, which force seekers to give more incentives to stimulate their internal motivation.

Second, it is positively related to the knowledge-sharing performance conversion rate, but negatively related to the solution cost reduction rate. This indicates that the main function of knowledge-sharing is to improve the performance of crowdsourcing, and its auxiliary role is to reduce the solution cost. In addition, the benefits brought by cost reduction are not sufficient to offset the increased cost of the knowledge-sharing incentive itself.

[15] The proof process of all results in this chapter is presented in Appendix.

Third, the improvement of the frequency of knowledge-sharing by the solver will not increase the knowledge-sharing incentives given by the seeker, but will instead cause the seeker to generate opportunistic psychology, thinking that knowledge-sharing behaviour does not require incentives.

Finally, although the increase in the number of solvers contributes to the occurrences of knowledge-sharing behaviour of solvers, it will reduce the incentive intensity from the seeker. Therefore, a larger crowdsourcing scale is not conducive to the revenue brought by the knowledge-sharing of the solver.

Result 3: When the condition of Result 1 is satisfied, $e_i^{NK5^*} = e_i^{K5^*}$, e_i^* is positively correlated with λ and negatively correlated with n.

Discussion: Result 3 indicates that the implementation of knowledge-sharing incentives will not affect the solver's private effort, but psychology of fairness concern will promote their private effort to increase the winning probability, which will also lead to the improvement of the solution performance. In addition, in view of the existence of the competition effect of the solver, regardless of whether or not to provide knowledge-sharing incentives, the level of private effort will definitely decrease with the increase in the number of solvers.

Result 4: Under the condition of Result 1, there are: (1) $s_i^{NK5^*} > 0$, $s_i^{NK5^*}$ is negatively related to λ and negatively related to n; (2) $s_1^{K5^*}$ is negatively related to λ, negatively related to n and not related to e; (3) $s_1^{K5^*} - s_i^{NK5^*} > 0$, $s_i^{K5^*} - s_1^{NK5^*}$ is positively correlated with λ, and positively correlated with n.

Discussion: Result 4 summarises the influencing factors of the knowledge-sharing effort level of the solver in the crowdsourcing community. First, even if the seeker does not implement knowledge-sharing incentives, the solver will choose to share knowledge due to the effect of cost reduction. This expands the research conclusion of Hao, Hou and Zheng (2016). Second, the existence of fairness concern will reduce the level of knowledge-sharing efforts of the solver. Obviously, knowledge-sharing increases the probability of other solvers' "free-riding" behaviour, which makes them feel "jealous", and the willingness to share knowledge is significantly reduced. This reveals the relevant phenomenon in the background to this chapter. Third, the increase in the number of solvers will not only reduce their private effort, but also reduce their input in knowledge-sharing for the result of competition.

The result also shows that, compared with the mechanism without knowledge-sharing incentives, implementing knowledge-sharing incentives can significantly improve the level of knowledge-sharing efforts of the solver. In addition, this promotion effect is positively regulated by the sensitivity of the fairness concern and the number of solvers. Therefore, from the perspective of enhancing the shared knowledge stock in the crowdsourcing community, it is the best choice for the seeker to guide the solver with a strong fairness concern to join and appropriately increase the task scale. On the other hand, when the seeker provides knowledge-sharing incentives, the frequency of knowledge-sharing observed by the seeker does not increase the solver's actual knowledge-sharing behaviour. In other words, the solver will not get a higher profit by only improving the "external action" of knowledge-sharing.

Result 5: If the condition of Result 1 is satisfied, the following are obtained:

- If $\frac{1}{\beta_k} > \frac{c_e(n+1)(n-1)}{hn^2}$, $E(V^{NKS^*})$ and λ are positively correlated; if $\frac{1}{\beta_k} < \frac{c_e(n-1)}{hn}$, $E(V^{NKS^*})$ and λ are negatively correlated; if $\frac{c_e(n-1)}{hn} < \frac{1}{\beta_k} < \frac{c_e(n+1)(n-1)}{hn^2}$, $E(V^{NKS^*})$ and λ are positively correlated first and then negatively correlated.
- If $\frac{1}{\beta_k} > \frac{c_e(n+1)(n-1)}{2hn^2}$, $E(V^{KS^*})$ is positively related to λ; if $\frac{1}{\beta_k} < \frac{c_e(n-1)}{2hn}$, $E(V^{KS^*})$ is negatively related to λ; if $\frac{c_e(n-1)}{2hn} < \frac{1}{\beta_k} < \frac{c_e(n+1)(n-1)}{2hn^2}$, $E(V^{KS^*})$ and λ are positively related first and then negatively related.
- $E(V^{KS^*}) > E(V^{NKS^*})$, and $E(V^{KS^*}) - E(V^{NKS^*})$ is always positively correlated with λ.

Discussion: Result 5 illustrates the performance contribution of knowledge-sharing incentives under the fairness concern. Regardless of whether the seeker implements the knowledge-sharing incentive mechanism, whether the fairness concern helps improve the task performance depends on the ratio between the conversion rate of private effort performance and the conversion rate of knowledge-sharing performance ($\frac{1}{\{3k}$).

When the ratio ($\frac{1}{\{3k}$) is high, fairness concern helps to improve the task performance, and when it is low, the result is the opposite. This is because the task performance is determined by both the solver's private effort and the shared knowledge stock in the community. When the private effort performance conversion rate is relatively higher, the former contributes more than the latter. Also, when combining Results 2 and 3, the impact of fairness concern on the two types of effort shows that the task performance is positively related to fairness concern sensitivity in the above condition.

When the ratio is low, the result will be the opposite.

When the ratio is moderate, the task performance rises first and then decreases with the increase of the fairness concern's sensitivity. So, there must be an optimal fairness concern degree that can maximise the task performance. This shows that when the marginal performance contributions of the two efforts are similar, the fairness concern will adjust the ratio of the two efforts in the performance contribution.

Result 5 also shows that solvers' fairness concern must help to improve the performance increment of KS relative to the NKS mechanism. Because knowledge-sharing incentives do not help improve the private effort of the solver, this shows that the negative impact of fairness concern on the knowledge-sharing behaviour under the KS mechanism is lower than the NKS mechanism. Therefore, from the perspective of maximising the performance value (i.e. relative task performance) of KS, the seeker should attract more solvers with strong fairness concern to participate in SMEs CCI task and join the knowledge-sharing crowdsourcing community. However, this does not necessarily improve the absolute task performance. The seeker should also consider the conversion rates of the two types of effort performance. Only when $\frac{1}{\{3k}$ is high can the absolute performance be improved simultaneously with the relative performance.

Result 6: When the condition in Result 1 is satisfied, the following are obtained:

- $^{K5}{*} - {}^{NK5}{*} > 0$, and $^{K5}{*} - {}^{NK5}{*}$ is positively related to λ.
- When $1 > max\left[\frac{(n-1)}{2n\hbar}\{3kc_e + \frac{(n-1)}{2n\hbar}k^2c_e^2, \frac{(n-1)(n+1)}{2n\hbar n}\{3kc_e + \frac{(n-1)}{2n\hbar n^2(n+1)}k^2c_e^2\right]$, $^{K5}{*}$ is positively related to λ; when $1 < (\frac{n-1)(n+1)}{2n\hbar n}\{3kc_e + \frac{(n-1)}{2n\hbar n^2(n+1)}k^2c_e^2$, $^{K5}{*}$ is negatively related to λ; in other conditions, $^{K5}{*}$ and λ are first positively related and then negatively related.

Discussion: Result 6 summarises the value of fairness concern and KS mechanism to the SME seeker from the perspective of economic benefits.

First, although knowledge-sharing incentives result in a certain cost, under the condition that the incentive mechanism is established, the improvement of task performance can fully offset this expenditure. Therefore, the expected economic benefits of the seeker under the KS model must be higher than the NKS model.

Second, the relative economic value of the KS mechanism to the seeker (that is, the difference between the economic benefits of the two incentive models) is positively related to the fairness concern. Therefore, it is more helpful to highlight the relative value of the KS mechanism in the crowdsourcing community where the solver has strong fairness concern. However, from the perspective of the absolute economic benefits of the seeker, the fairness concern is not necessarily beneficial, which is influenced by the ratio of $\frac{1}{\{3k}$. When the ratio is large, the contribution of private efforts to the task performance is high, and the absolute economic benefits of the seeker are positively correlated with the sensitivity of fairness concern. The result in other situations may be the opposite.

5.6 Numerical Simulation

It can be seen from Table 5- 1 that the solver's expected economic benefits expression is complex, so this section uses numerical simulation to study the solver's economic benefits. Also, further analysis of the relative economic value of knowledge-sharing incentives for the solver is shown, and how it changes with fairness concern sensitivity and the number of solvers. Hao, Hou and Zheng (2016) illustrate an example assuming the private effort cost coefficient $c_e = 0.2$, the knowledge-sharing cost coefficient $h = 0.1$, the Gumble distribution scale parameter $\mu = 2$, and the fixed bonus $A = 5$.

First, setting the number of solvers $n = 8$, analysing the relationship between the π_i^{KS} and λ under different ratios of $\frac{\eta}{\beta k}$. Second, setting $\eta = 0.8, \beta = 0.4, k = 0.2$, exploring how the changing trends of π_i^{KS} and n are affected by λ. Figure 5-2 and Figure 5-3 are, hence, obtained.

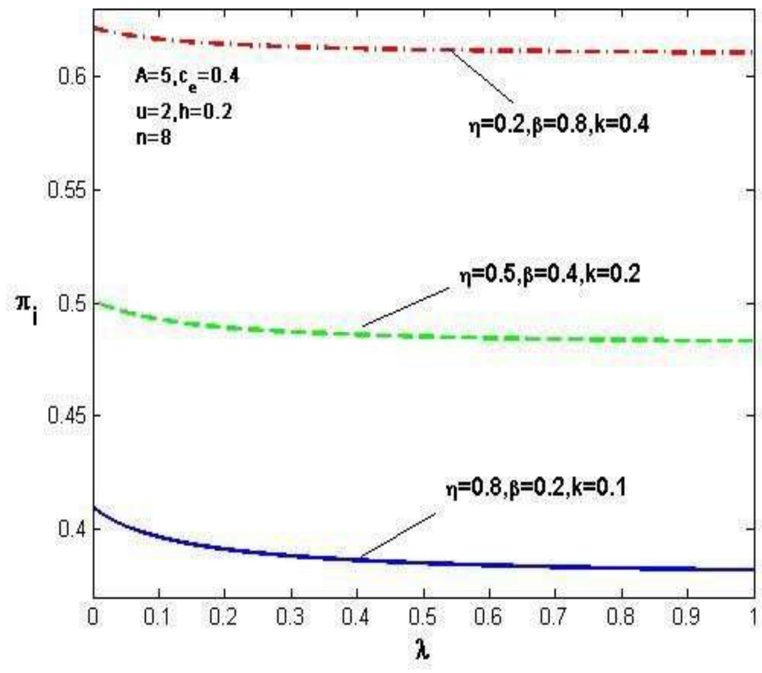

Figure 5-2 The impact of fairness concern sensitivity on solvers' expected return

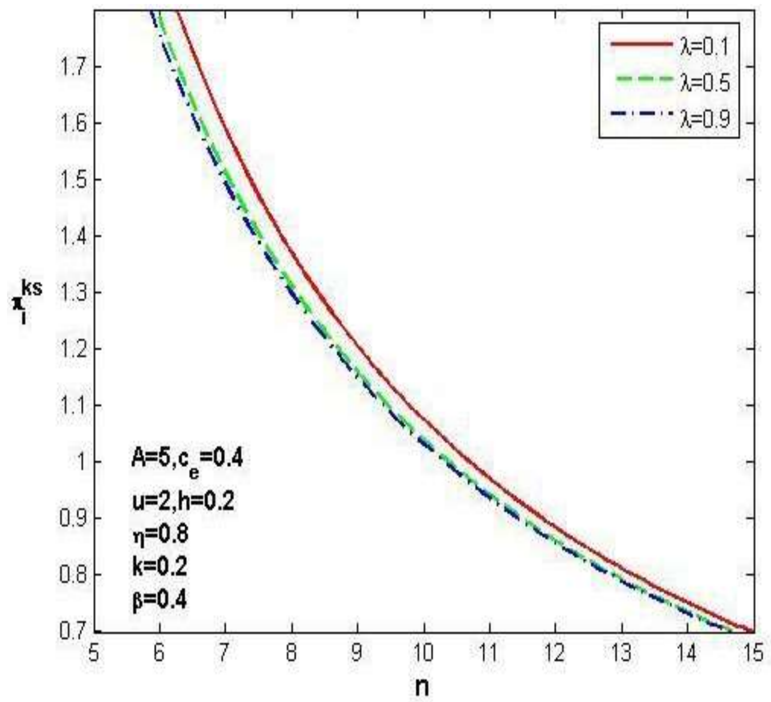

Figure 5- 3 The impact of the number of solvers on solvers' expected return

Seen from Figure 5- 2, under the KS model, no matter what the value of $\frac{1}{\beta k}$ is, $\pi_i^{KS^*}$ always declines with the increase of λ, but the downward trend gradually flattens. This shows that fairness concern is not conducive to the solver's economic benefits. The reason is that, on the one hand, fairness concern will stimulate the solver to invest more in private effort while not increasing the winning probability under homogeneous conditions. On the other hand, the solver's knowledge-sharing incentive revenue will also be decreased due to the existence of fairness concern. However, with the increase of knowledge-sharing incentive intensity (b), this negative effect will gradually disappear as the sensitivity of fairness concern increases. It can also be seen from Figure 5- 2 that the larger the $\frac{1}{\beta k}$, the lower the solver's expected return curve. In other words, the higher the contribution of private efforts towards the task performance, the smaller the expected economic benefits for the solver. This fully shows that the revenue of knowledge-sharing occupies a relatively high proportion in the solver's economic benefit. In addition, from Figure 5- 3, the increase in the number of solvers will reduce the expected economic benefit for each solver. However, it will weaken the negative effect of fairness concern on the economic benefit, which will cause the seeker to pay more attention to the community size.

Finally, discussing the relative economic value $\pi_i^{K5} - \pi_i^{NK5}$ of the KS model for the solver, as well as the adjustment effect of the fairness concern sensitivity and the number of solvers, the result is shown in Figure 5-4. It can be seen that the $\pi_i^{K5} - \pi_i^{NK5}$ curve is always above the 0 axis, that is, the KS model will bring more economic benefit to solvers than the NKS model. This also reflects that although fairness concern will weaken the solver's motivation of knowledge-sharing, it is conducive to improving the knowledge-sharing incentive intensity and enhancing the economic value of solvers. Combined with Results 5 and 6, the KS incentive mechanism can achieve a "win-win" between the seeker and the solver, and the degree of "win-win" increases with increasing fairness concern. Therefore, for the organisers of crowdsourcing communities, it is necessary to implement knowledge-sharing incentives, in order to further enhance the value of knowledge-sharing incentives in the economic benefits of crowdsourcing bodies and the task performance.

In addition, from the position and shape of the three curves in Figure 5- 4, it is found that the larger the n, the lower the curve position, the gentler the upward trend, and the smaller the curve spacing. This shows that competition caused by the scale of the crowdsourcing task will decrease the relative economic value of solvers, but this negative effect of scale will gradually decrease.

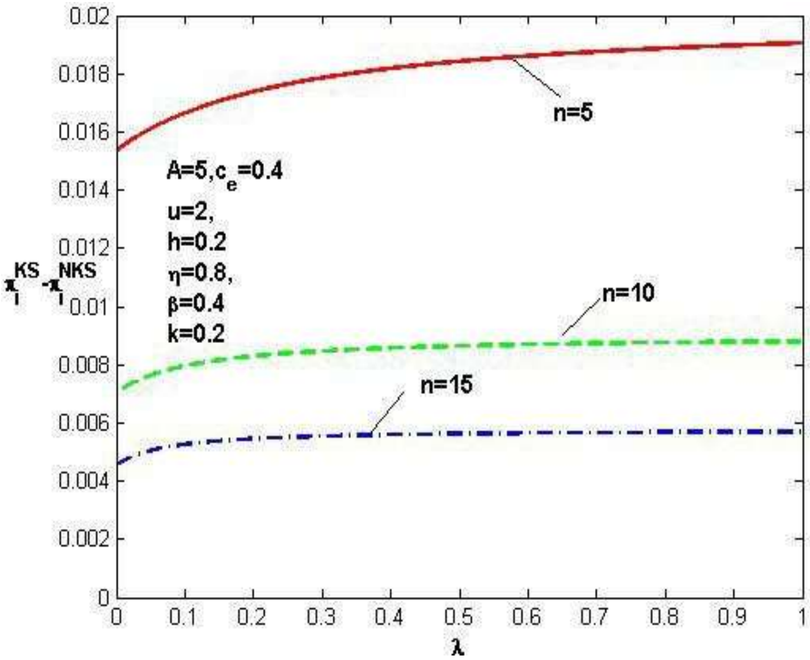

Figure 5- 4 The impact of fairness concern sensitivity and the number of solvers on the economic value of knowledge-sharing incentives

5.7 Research Limitations and Reflection

5.7.1 Research Limitations

● The horizontal fairness concerns among the solvers are considered in the model. But, the vertical fairness concerns between the seeker and the solvers are ignored.

● The solvers are assumed to be homogeneous, however, the ability of each solver in transforming shared knowledge into crowdsourcing performance is different.

● Only when the type of crowdsourcing is a creative contest, the performance formula proposed is valid. But, in a professional contest, the performance function and the winning probability will show a significant difference.

5.7.2 Reflection

In response to the questions posed in the Introduction:

Question (1): In view of the important role of knowledge-sharing on innovation, can the knowledge-sharing behaviour of the solvers improve their winning probability in CCI that is characterised by “winner-takes-all”?

It is for sure that the knowledge-sharing behaviour of the solvers cannot improve their winning probability, because all the solvers can benefit from the shared knowledge.

Question (2): If not, what incentive mechanism should the taken by organisers in the crowdsourcing community to stimulate the knowledge-sharing behaviour of the solvers?

The decision makers/organisers should observe and evaluate the knowledge sharing behaviour of the solvers in the crowdsourcing community, and give linear material rewards according to the degree of knowledge sharing determined by their sharing frequency and content.

Question (3): How is the value of the knowledge-sharing incentive mechanism, the crowdsourcing performance and the economic benefits of both the seekers and solvers, affected by the psychology of fairness concern?

Fairness concern can certainly reduce the knowledge sharing behaviour and economic benefits of the solvers, but they do not necessarily reduce the crowdsourcing performance and the economic benefits of the seeker.

5.8 Conclusions

This chapter discusses a knowledge-sharing incentive mechanism in the crowdsourcing community based on the reasonable evaluation of the solvers' knowledge-sharing behaviour through observable behaviour frequency, whose specific process is shown in Figure 5- 1. Then a knowledge-sharing incentive mechanism model (KS) under solvers' fairness concern is established and solved based on game theory, and the model results are compared with the non-knowledge-sharing incentive mechanism model (NKS). Results show that, also, the knowledge-sharing behaviour cannot improve the winning probability of each solver; the KS model is conducive to improving the performance of CCI to achieve a win-win situation for both the seeker and solvers. Furthermore, solvers' fairness concern helps to increase the economic motivation for the seeker to implement the KS model, and increase the rewards it pays for the mechanism, but reduce solvers' motivation for knowledge-sharing efforts. It is also found that whether fairness concern contributes to the improvement of crowdsourcing performance and the economic benefits of the seeker, it depends on the value of $\frac{1}{\{3k}$, while the relative economic value of the KS model will always rise with the grow of the solvers' fairness concern.

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6 ANALYSIS ON THE EFFECTIVENESS OF INCENTIVE MECHANISMS OF SMES CROWDSOURCING CONTEST INNOVATION

Abstract

Is the key to success of crowdsourcing contest innovation to build an effective incentive mechanism? As part of this chapter it is attempted to answer this critical question by analysing first-hand data from web crawlers and combining these findings with a large amount of second-hand data from official crowdsourcing contest innovation platforms. By doing this, it begins to reveal interesting connections about the practical operation processes that could help towards explaining the effectiveness of the incentive mechanism for SMEs to participate and engage via crowdsourcing innovation platforms.

The results of this chapter conclude that monetary incentive, reputation incentive and knowledge sharing incentives are used as a mechanism for popular crowdsourcing contest innovation platforms, and the explicit and implicit incentive effect, tactical effect and strategic effect of the incentive mechanism are leveraged by successful innovation platform providers. A critical review of incentive mechanism deficiencies is also carried out, including topics related to pricing services, refining task distribution and divisions, supervision and reward systems, and evaluation of schemes.

Keywords: crowdsourcing contest innovation platforms; effectiveness analysis; guarantee measures; web crawling

6.1 Introduction

As the practice of crowdsourcing continues to deepen, the incentive of crowdsourcing contest innovation (CCI) has gradually become the focus point of many academic communities. Most of the existing literature centers on theoretical incentive mechanism design and theoretical analysis of incentive performance. Discussing how to improve the performance of crowdsourcing and the economic benefits of both the seekers and solvers by improving the innovative efforts of the solvers. For example, Wan (2020) constructed a two-stage mobile crowdsourcing network dynamic incentive mechanism design based on contract theory to promote users to participate in long-term mobile crowdsourcing tasks. However, whether the incentive mechanism designed at the theoretical level is really effective must be tested in practice. In other words, what are the current task characteristics and operating procedures on the existing crowdsourcing platforms where SMEs publish their crowdsourcing contest tasks? Are the incentives such as material incentive, reputation incentive, and knowledge sharing incentive effective on the crowdsourcing platforms? What kind of safeguard measures should be taken to solve the defects in the existing incentive mechanism and improve its effectiveness? The answers of these problems have important practical significance for improving the performance of SMEs crowdsourcing contest innovation.

Hence, this chapter collects a large amount of primary and secondary data on the crowdsourcing platform through web crawlers, official website data and other means, and conducts a detailed analysis of the incentive mechanism of the platform in order to solve the issue of the effectiveness of its incentive mechanism.

6.2 Research Methods

6.2.1 Research Sample Selection

According to the principles of sample selection (Zapata-Barrero and Yalaz, 2018; Sun *et al.*, 2019), Zbj.com is selected as the research sample.

First, importance and representativeness principle. Zbj.com is currently China's largest e-commerce service trading platform. In 2011, Zbj.com obtained IDG investment[16] and was selected as the "Top Ten Best Business Model" enterprise in China that year. And now it has become the largest crowdsourcing service trading platform for SMEs in China[17].

Second, theoretical sampling principle. The objects of Zbj.com include the seekers, the solvers and the platform itself which has always been studied separately: seekers are SMEs, solvers are talents in brand design, marketing planning, website development, e-commerce services, and the platform has long since transformed from a single platform provider to a facilitator and regulator. The three main bodies are of considerable importance to the improvement of the overall efficiency of crowdsourcing contest. In this context, the role of their incentive mechanism will also be fully revealed.

Third, objective consistency principle. Most of the tasks of Zbj.com come from SMEs. As for the crowdsourcing tasks issued by SMEs, the difficulty of completing each task is relatively low and the resource consumption is also not that high. The solvers win the crowdsourcing contest by quality (in the piece counting mode, the solvers win by quantity). Furthermore, how Zbj.com can improve the completion efficiency and effect of the task is consistent with the goal of this thesis to build an effective incentive mechanism and improve the overall efficiency of SMEs CCI.

6.2.2 Data Collection

Research data are collected in the following ways:

● Web crawling: utilising the Requests (an elegant and simple HTTP library for Python, built for human beings)[18] to write the crawler program. The captured content includes service provider's (the solver's) name, service provider's level, store rating, applause rate, transaction price, transaction time, number of solvers, task category, and so on.

[16] https://www.idgcapital.com/
[17] https://xw.qianzhan.com/analyst/detail/329/190916-f5869e52.html
[18] https://requests.readthedocs.io/en/master/

● Reading and sorting out a large amount of second-hand data on the official website of Zbj.com, including the examples of excellent solvers, and the rules and regulations of the platform.

● The author is registered as the seeker and solver of the platform to get familiar with the operating process of the platform.

6.3 Analysis of Operation Modes

There are four main operation modes considered a part of this chapter: reward contest, bidding, piece counting, and collaborative "challenge".

6.3.1 Reward Contest Mode

The reward contest mode is also called pitch mode, which requires the solver to submit the solution first. The specific process is as follows:

Step 1: The details and requirements of the task is issued by SMEs on the platform, including the task type, budget amount, demand information, regional requirements, and time requirements, and at the same time, the reward is in escrow by the platform.

Step 2: After the identity confirmation by the platform, solvers sign up to participate in the task, complete it within the specified time and submit the solution to the platform.

Step 3: The platform forwards the solvers' solutions to the seeker.

Step 4: The seeker receives all the submitted solutions, organises experts/specialists to evaluate them, and then selects the most satisfactory solution according to the pre-set criteria.

Step 5: The seeker announces the winning solution. After the announcement, the intellectual property rights of the winning solver will be transferred to the seeker. Besides, most of the reward goes to the winning solver, and the platform collects a small portion of the reward as a commission. The intellectual property rights of the unsuccessful solutions still belong to the solvers. The operation flow of this mode is shown in Figure 6-1.

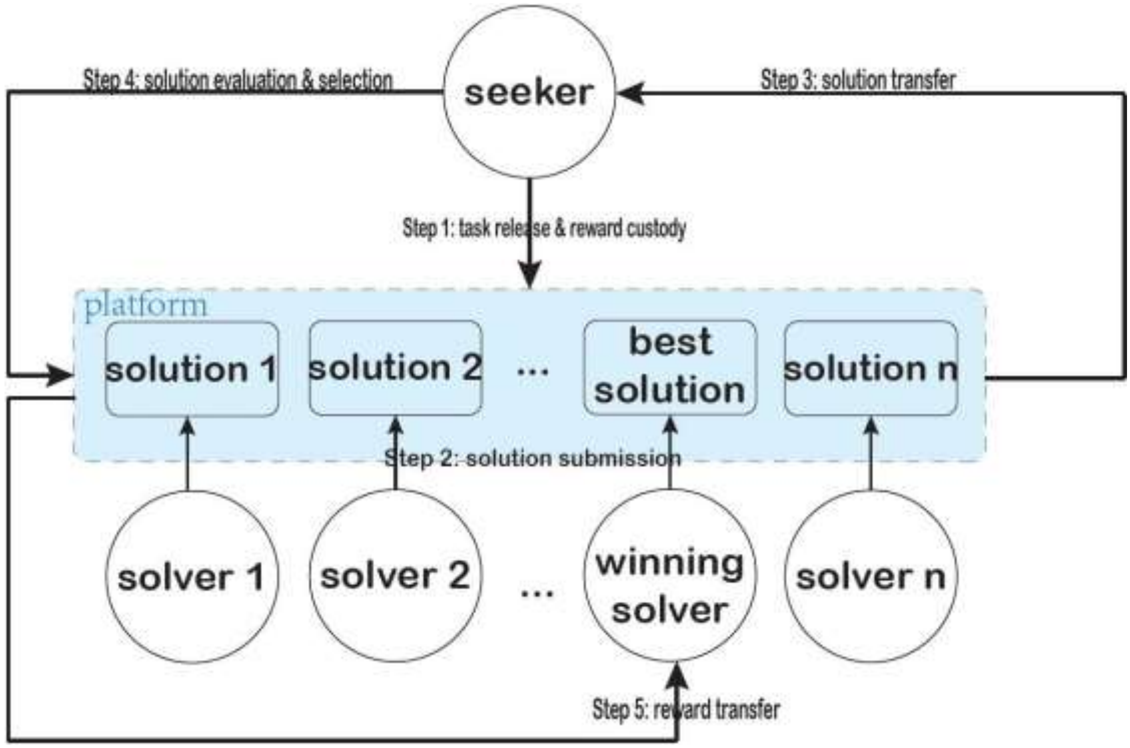

Figure 6-1 Operation flow chart of reward contest mode

(summarised by the author)

In the entire process, seekers and solvers stay in a non-anonymous system, and both parties can obtain important information such as the contact information and communicate in real time through online chat tools, such as WeChat. The winner will not only get a cash reward, but also have the opportunity to be displayed in the "Ranking List"[19] regularly published on the platform. Because the reward contest mode requires submission of the solution first, so it is more suitable for creative tasks such as corporate slogan design, LOGO design, and personal naming.

[19] https://www.zbj.com/rank/ppsj?floor=sale&fr=sysitemap

6.3.2 Bidding Mode

The bidding mode is another important operation mode on the platform. In this mode, SMEs publish the demand on the platform while solvers need to pay a certain fee to be eligible to bid. The essential difference between bidding mode and pitch mode is that solvers only need to submit ideas instead of making complete solutions. The operation flow of bidding mode is shown in Figure 6- 2.

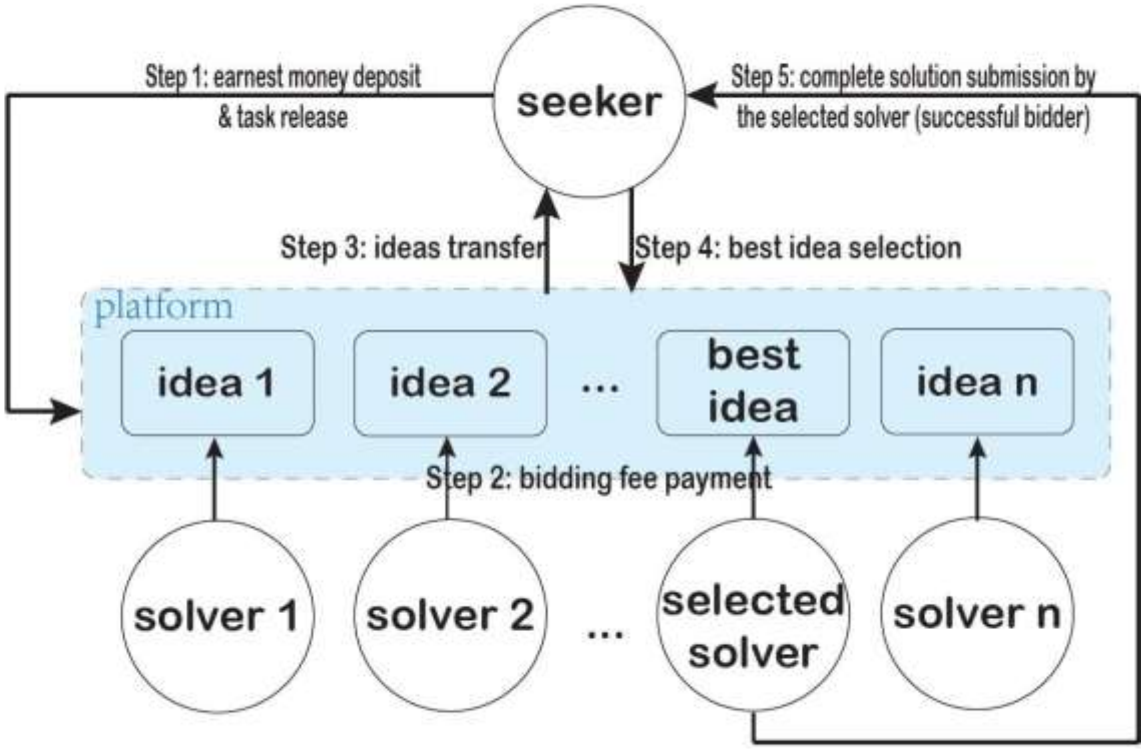

Figure 6- 2 Operation flow chart of bidding mode

(summarised by the author)

For more complex tasks that cannot be solved by inspiration and wisdom alone and require solvers to have more professional skills such as designing and programming, the seeker generally adopts the bidding mode. In this mode, the seeker can accept more excellent solutions, and can choose one of the best solutions to pay the bonus while drawing on other solutions for free. Obviously, it will bring certain intellectual property rights risks to solvers. As a result, the participation of solvers is significantly lower than the reward contest mode.

6.3.3 Piece Counting Mode

The selection and reward in piece counting mode are based on the number of solvers' solutions that meet the seeker's requirements and unit price of the piece is set by the seeker in advance. In this mode, whether the solution is qualified or not is mainly decided by the seeker, and the number of qualified solutions is totally determined by the seeker's demand. For the difficulty of piece counting mode is low, the number of solvers in this mode is much higher than reward contest mode and bidding mode. The reward in each qualified selected solution is very small, which are less than 10 RMB in some tasks. Since the value of the economic benefits is relatively limited, and the characteristics of "competition" cannot be fully reflected, so this mode is temporarily ignored in the analysis later in this research.

6.3.4 Collaborative "Challenge" Mode

For some of the more important and complex crowdsourcing tasks, the platform allows the seeker to achieve high-quality solutions in the mode called collaborative challenge (for example, Jaguar "the art of performance tour"[20]), which has the following features:

- The task in this mode is usually very important and difficult, with the "modularity" feature.
- Solvers are generally experts in various fields with strong professional skills.
- The reward amount is much higher than that of general reward contest mode, usually reaching more than 20,000 RMB[21].
- The solvers are allowed to participate in the form of teamwork.
- The task types involve all stages from creativity to prototype to practice.

[20]https://shop.zbj.com/works/detail-wid-88992.html?fr=sx_9&pdcode=9&sxid=3959667&pos=2&ym=1&pst=searchp-list-window-1-2
[21] https://dasai.zbj.com/

The features of different task types in collaborative “challenge” mode are shown in Table 6-1.

Table 6-1 Comparisons of different task types of collaborative “challenge” mode

Task type	Period	Reward amount (RMB)	Ownership of intellectual property rights (IPR)
Logo creative contest	from days to 2 months	20,000-100,000	IPR transferred to the seeker after paying the bonus
Slogan solicitation contest	1-2 months	20,000-100,000	IPR transferred to the seeker after paying the bonus
Golden idea creative contest	0.5-1 month	20,000-100,000	IPR transferred to the seeker after paying the bonus
Mascot creative contest	1-2 months	50,000-100,000	IPR transferred to the seeker after paying the bonus
Lyrics creative contest	1-2 months	50,000-100,000	IPR transferred to the seeker after paying the bonus

This mode is an important mode for team participation in crowdsourcing contest. Each team sets up a team leader who recruits individual solvers with various knowledge and skills, and then forms a team task room to create solutions in a team collaboration manner. In order to get high-quality solutions, the platform provides an innovative management platform, including the basic task room, the anonymous communication function between the seeker and solvers, and the solvers’ collaboration function. Each solver has a separate “task room” from which all information related to the task can be obtained. All task rooms of the same task will be connected to the same background program to facilitate solvers to directly submit solutions. In addition, the platform provides a discussion forum as well as communication tools for exchanging ideas among solvers. Meanwhile, a “black box” of anonymous communication between the seeker and solvers are also generated. The details are shown in Figure 6-3.

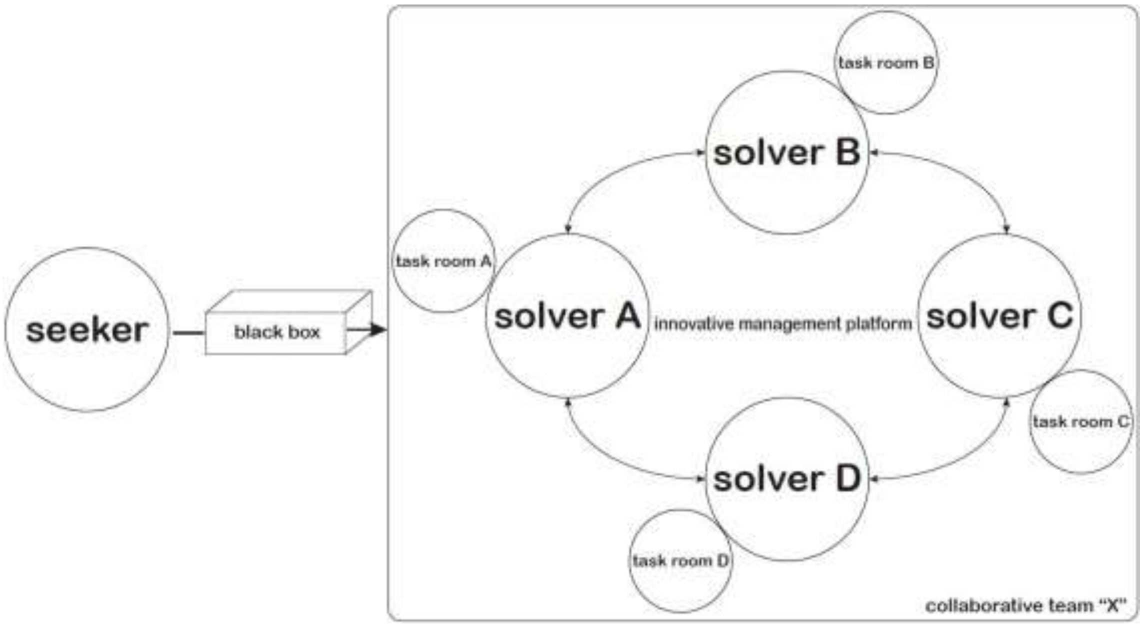

Figure 6- 3 Schematic diagram of collaborative "challenge" mode

(summarised by the author)

6.4 Analysis of Incentive Ways

6.4.1 Monetary Reward

<u>Single people monetary reward</u>

Single people monetary reward refers to a transaction in which the seeker only selects one solution as the winning solution, and the money only goes to the single solver who offers the winning solution. Without a doubt, this reward mode is conducive to inspiring the solver to pay as much as their wisdom and creativity, so that the seeker can obtain high-quality solutions. From the perspective of operation mode, all the bidding mode and a high portion of pitch mode tasks using this reward means. The details are shown in Figure 6- 4.

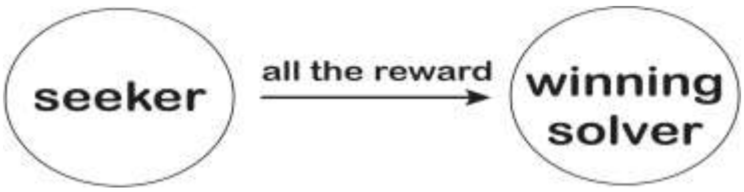

Figure 6- 4 Schematic diagram of single people monetary reward

Multi people monetary reward

Generally, multi people monetary reward generally exists in reward contest mode and piece counting mode. The award setting is fixed, which only can be divided into three grades: first, second and third. But the proportion of each grade of award to the total award is not fixed. The proportions will be determined by the seeker according to the quality of the winning solvers[22]. Figure 6- 5 shows an example of the allocation of the reward. Obviously, compared with single people monetary reward, the winning probability in this mode is greatly increased, which objectively lowered the threshold for participation, and plays a positive role in attracting solvers and increasing the popularity of task.

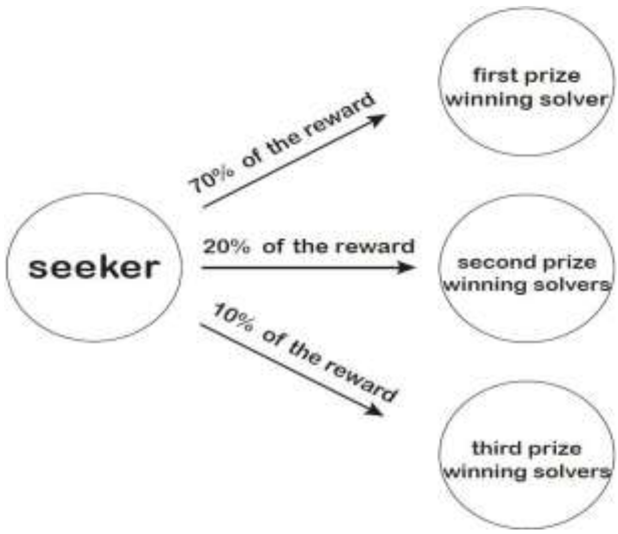

Figure 6- 5 Schematic diagram of multi people monetary reward

Specially, the multi people monetary reward can also be applied in the collaborative challenge mode, in which members in one team have the opportunity to be rewarded. The reward distribution plan generally has the following two options: (1) Equal payment; (2) Half is equally distributed by team members, and the rest half is decided by the team leader.

[22] https://rule.zbj.com/ruleshow-0?pid=135&categoryId=278

6.4.2 Reputation Incentive

Reputation is a comprehensive evaluation of knowledge, skill, review and credibility which plays an important role in the realisation of the value of seekers and solvers. Generally speaking, the higher the reputation of the solver, the higher the winning probability, and the greater the monetary reward. On the platform, solvers' reputation is displayed in the form of grade & point. The higher the grade and point, the higher the solver's ranking in the witmap (short for witkey map, which refers to the search engine about solvers formed by aggregating the four most important attributes of solvers' geographic location, professional expertise or interests, contact information, and brain mapping area through the Internet), the more intelligently matching the task can be achieved, the higher the probability of winning the task, and the better the expected monetary reward (Figure 6- 6).

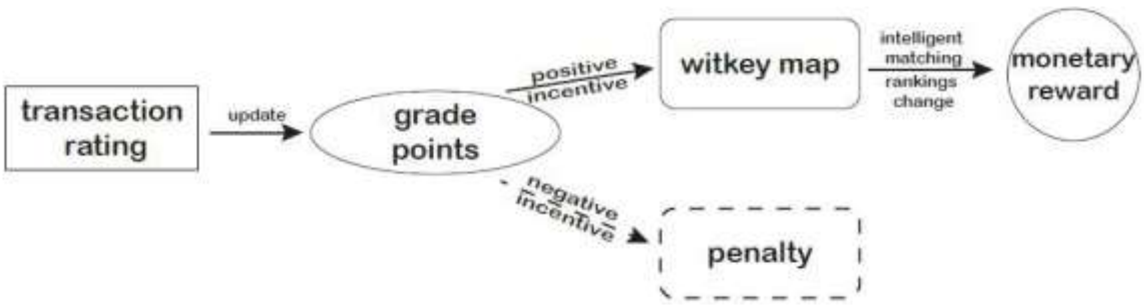

Figure 6- 6 Flow chart of reputation incentive on the platform

<u>Grade & point</u>

On the platform, reputation incentive is reflected in grade and credit point system.

● *Grade:* The growth value that determines the grade of the solver is accumulated from the growth value obtained in each task[23]. The calculation is a bit complicated, and there are two rules: basic rules and acceleration rules. The basic rule is growth value = transaction amount * growth factor. The growth factor comes from the transaction evaluation of the seeker. When the comment

[23] https://rule.zbj.com/ruleshow-0?pid=629&categoryId =303

is favourable, the growth factor is 1; when the comment is neutral, the growth factor is 0.5, and for negative comment, the growth factor is 0. The acceleration rule means that the growth factor increases with the length of the content of the favorable review, repeat customer transactions and high-quality evaluations of the seeker. For example, a repeat customer transaction refers to a non-multi-person transaction with a certain seeker for 2 or more times. The positive review after the second time transaction will increase the growth factor by 0.1 on the original basis. The grade of solvers varies from new solver (Grade 0) to “Zhu Yijie” (Grade 1) and to “Zhu Bashiyijie” (Grade 81). And the growth value required for level promotion tends to accelerate as the level increases.

● *Point:* Precisely, credit point, represents the solvers’ code of conduct set by the platform. Whether it is an individual, an enterprise or an organisation, real identity information must be provided for registering on the platform. Moreover, enterprises must also provide main information such as business type, business scope, registered capital, and contact persons. Once the registration is completed and passes the audit, the users (both the seeker and solver) can get 100 initial points. When seekers and solvers violate the rules in the transaction process, the platform will deduct some or all of the credit points based on the different violations and record them. For seekers, high point indicates that seekers are honest in review and payment, so their future tasks will have more solvers to participate. For solvers, high point not only means that they have strong creative ability, but also shows that they are with a high degree of integrity in completing the task and will have more opportunities to win the task in the future. What’s more, the credit point is the main basis for negative incentives on the platform. That is, the platform reserves the right to restrict the participation in various activities on the platform when the users cannot meet the designated standards. When the accumulated deduction points reach a certain amount, users will be given different levels of penalties[24]. The details are shown in Table 6-2.

[24] https://rule.zbj.com/ruleshow-27?categoryId=157&pid=158

Table 6- 2 Penalty rules based on users' points

Deducted points	Penalty and limitation					
	Prohibition of releasing new tasks (days)	Prohibition of bidding (days)	Prohibition of participating in marketing activities (days)	Prohibition of the purchase of advertising (days)	Cancellation of business opportunity push (days)	Account close (days)
20	7	7	7	7	7	7
20-40	15	15	15	15	15	15
40-60	30	30	30	30	30	30
60-100	60	60	60	60	60	60
100	Account closed permanently					

Witmap

Witmap is an important matching mechanism of reputation on the platform. It distinguishes all solvers according to factors such as geographic location, professional expertise, interest, witkey space and grade points, and forms a search engine for solvers based on these factors. The seeker can immediately query the corresponding solver or intellectual product by entering the corresponding task or skill keywords. An important factor that determines the results of Witmap or the system's automatic matching result is grade and point. Generally speaking, solvers with higher level grade or point are more likely to get the top ranking on Witmap and are more likely to win the task. In order to obtain higher points, solvers must go all out during each task to obtain an excellent review.

6.5 Analysis on the Effectiveness of the Incentive Mechanism

6.5.1 Both Explicit and Implicit Incentives Matter

Explicit incentives

Explicit incentives refer to the compensation given by seekers to solvers according to the standard and pre-set agreement, as well as the satisfaction brought by crowdsourcing task itself to solvers. the explicit incentives of the platform are divided into monetary reward and the task itself.

● *The effectiveness of monetary reward:*

The display of the clear award amount increases the solvers' participating motivation. It is found that seekers must attach the reward amount when they submit the task on the platform while the platform also clearly announces the commission ratio of various tasks. Therefore, solvers are clear about the amount of reward they are going to get which reduces the uncertainty of value output and has a significant positive effect on attracting solvers to join in the task.

However, there is uncertainty between the amount of task reward and the solvers' behaviour. Data of 383 crowdsourcing contest tasks were collected from the platform through web crawler. Among them, 226 tasks are in the category of reward contest, 115 tasks in the bidding category, and 42 tasks in the collaborative challenge category. The tasks of reward contest mode and bidding mode were divided into three groups according to the amount of the bonus, which are above 3,000 RMB, 1,000-3,000 RMB and below 1,000 RMB. And the correlation analysis was conducted between the amount of the bonus and the number of solvers. Results are shown in Table 6- 3.

Table 6-3 Correlation analysis between the task bonus and the solvers' number

	Reward contest			Bidding		
Bonus (RMB)	>3,000	1,000-3,000	<1,000	>3,000	1,000-3,000	<1,000
Task number	77	51	98	44	26	45
Correlation coefficient	0.056	0.33	0.947	-0.144	-0.006	-0.199
Sig. (2-tailed)	0.631	0.018*	0.000**	0.353	0.976	0.19
Task proportion	34.10%	22.60%	43.40%	38.30%	22.60%	39.10%

Note: *95% confidence interval excludes the null value; **99% confidence interval excludes the null value.

It can be seen that tasks with a bonus amount of 0-3,000 RMB accounted for the highest proportion. In the reward contest tasks, there is a strong positive correlation between the number of solvers and the reward amount in the range of less than 1,000 RMB; within 1,000-3,000 RMB, although there is still a correlation between the number of solvers and the amount of reward, the significance has weakened; above 3,000 RMB, there is no correlation at all. This shows that the monetary incentive is only effective in scenarios where the task amount is low. Obviously, for crowdsourcing contest tasks that reward are more than 1,000 RMB, the increase in the amount of reward means a significant increase in the complexity of the task and skill requirement which result in the reduction of monetary effectiveness. However, for bidding mode tasks, no matter in which interval, the amount of the reward and the number of solvers is not related. This is because the only winning bidder is completely appointed by the seeker, and there is no first draft selection stage in the bidding mode, which increases the concern of the solvers about the "cheating" problem in the bidding process. In addition to the payment threshold of the bidding mode, monetary incentive does not significantly increase solvers' motivation.

Besides, the monetary reward methods will also have a certain impact on the effectiveness of the monetary incentive. Although the crowdsourcing contest mode provides seekers with a variety of options, this model wastes the time and energy of the solvers who cannot win in the end. Especially for the single people reward method, the risk of resource waste is particularly prominent. The data of 383 tasks were calculated according to the two monetary reward methods – single people reward and multi-people reward, and Table 6- 4 was obtained.

Table 6- 4 Comparison of main effectiveness indexes of two monetary reward methods

	Applicable mode	Number of tasks	Task proportion	Average number of solvers	Satisfaction degree
Single people reward	reward contest, bidding, collaborative challenge	295	77.00%	48	80.60%
Multi-people reward	reward contest, collaborative challenge	88	23.00%	104	68.40%

It can be seen that the average number of solvers in the single people reward method is 48, far lower than the 104 people in the multi-people reward method. The multi-people reward method improves the chance of winning, so the number of solvers is significantly higher. However, due to the low bonus set by SMEs, the qualification requirements for solvers are not high, which means the low threshold for participation, so it will cause the “opportunistic” behaviour of low-skilled members. Furthermore, the sharing of bonuses will make it impossible for high-skilled solvers to invest in a higher level of innovation efforts. Therefore, the multi-people reward method is not necessarily conducive to highest quality solution (the satisfaction level of the seeker under the multi-people reward method is lower than of the single people reward method).

● *The incentive effectiveness of the task itself:*

In order to verify the incentive effectiveness of different task types, the data of all 383 tasks were counted according to the three task types (reward contest, bidding and collaborative challenge) respectively, the average reward amount of the task, the average number of solvers, and the average grade of solvers are displayed in Table 6- 5.

Table 6- 5 Statistical data on the effectiveness of task incentive

Task type	Task number	Average reward amount (RMB)	Average number of solvers of one task	Average grade of solvers of one task
Reward contest	226	1934	81	10
Bidding	115	4497	7	14
Collaborative challenge	42	11159	29.9 (including 2.1 teams)	19

From Table 6- 5, the reward amount and the solvers' average grade level of the collaborative challenge mode are much higher than the reward contest mode and bidding mode. According to Section 6.3, the difficulty of collaborative challenge is significantly higher than that of the other two operation modes; and for tasks of the same operation mode, their difficulty is usually manifested by the reward amount, so it is known that the higher the task difficulty, the fewer the number of solvers and the higher the level of solvers. This shows that the task itself cannot be ignored in the stimulation of the highly skilled solvers, which indicates that objective incentives are reflected on the platform. In addition, a few collaborative challenge tasks are issued by the government or non-profit organisations, with a feature of commonweal. For example, the Yunnan Leading Group for Cultural Industry Development has offered a reward of 200,000 RMB for improving the traditional craft of Jianshui purple pottery in 2014[25]. Participating in such tasks gives solvers great satisfaction in giving back to the community and fulfilling their social responsibilities. Figure 6- 7

[25] https://task.zbj.com/3883785/?pdcode=18

summarises the factors influencing the effectiveness of explicit incentives on the platform.

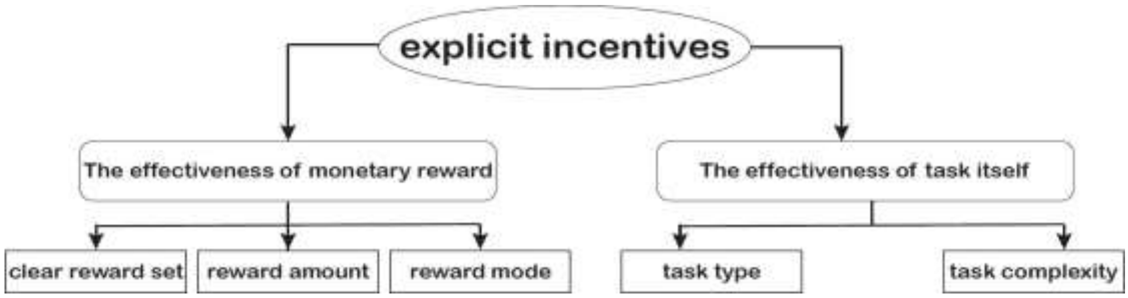

Figure 6- 7 Factors influencing the effectiveness of explicit incentives

<u>Implicit incentives</u>

Implicit incentives refer to the sum of non-public incentives received by solvers in an unperceived state. It cannot be quantified in the short term, and the effect will gradually manifest in the future. The effectiveness of the implicit incentives is mainly reflected in the following aspects.

● *Opportunities for improving innovation ability:*

Most tasks on the platform are of a creative nature and require intellectual input from solvers with knowledge and experience. Before tasks are released, seekers will elaborate on their quality standards, completion time and other important indicators. In addition, the platform gives solvers the training opportunity to develop their innovative ability. By participating in various crowdsourcing tasks, solvers do not only receive material rewards, but also greatly improve their own knowledge and skills.

● *Broadening the breadth of knowledge:*

The types of tasks on the platform include creative design services, marketing promotion, copywriting, life services, business services, industrial construction, program development services and other categories, covering life and so on. Diversity tasks give solvers chances to broaden the knowledge field.

In view of the spillover of creative knowledge, solvers' experience in the process of solving a problem in one field can bring a new perspective and method for the solution of a problem in another field.

The platform provides IM (instant message) tools, online community (called "Bajiequan")[26] and other tools for knowledge exchange. Solvers interested in a certain topic can communicate with others from another knowledge field through these tools.

● *Providing the possibility to build professional channels and find collaborative partners:*

For solvers, the biggest implicit incentive comes from the appreciation from the seeker. Most seekers on the platform are tech start-ups, and they have good development prospects. Solvers have the possibility of getting into large enterprises through the social networks of these tech start-ups. This effect comes from the "Outstanding Witkey Display" system launched by the platform[27]. The platform will regularly select some perfectly resolved task packages for display on the homepage, promote and track the outstanding "deeds" of solvers, and award solvers the title of "outstanding Witkey". This increases the solvers' sense of accomplishment while expanding their opportunities for being found by the enterprises, especially established ones.

From the above analysis, it can be seen that the explicit and implicit incentive effects are complementary, which are summarised in Figure 6- 8.

[26] https://quan.zbj.com/forum.php
[27] https://m.zbj.com/case/rank

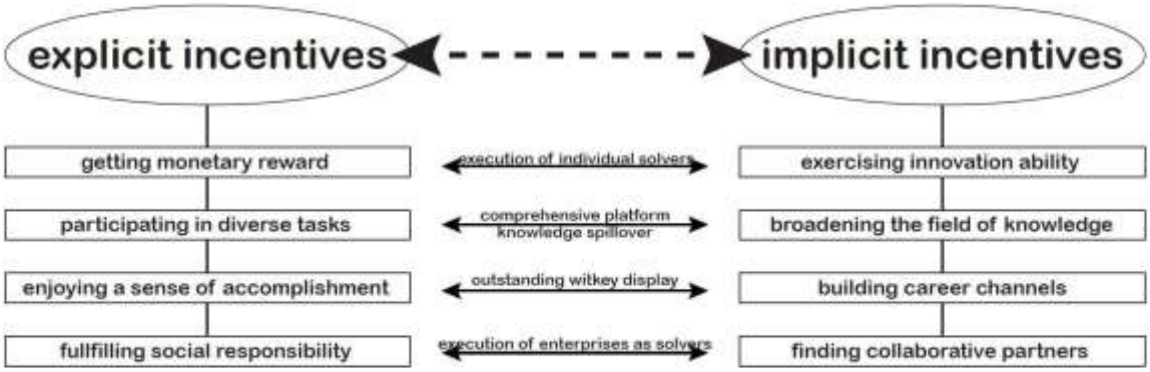

Figure 6- 8 The explicit and implicit incentive effects and their relationship

(abstracted by the author)

6.5.2 The Salience of the Synergistic Incentive Effect

The synergistic incentive effect on the platform includes two aspects: the synergy between seekers and solvers and the synergy among solvers.

<u>Synergistic incentive effect between seekers and solvers</u>

● *Initial synergistic effect:*

The advanced operation model and lower entry of the platform have attracted a large number of SMEs and solvers, while resulting in the uneven quality of users on the platform. It is difficult to ensure the normal progress of the transaction only by users' self-moral restraint, and opportunism is inevitable. A standardised resource identification mechanism has been designed on the platform to optimise the management of the platform. Specific practices include:

- Implementing real-name registration system.

- Setting the platform service rules and margin system, and clarifying the responsibilities of seekers, solvers and the platform.

- Providing assisting service – Guanjia Bajie[28] which is a brand-new member discount service for enterprises. According to the estimated

[28] https://gj.zbj.com/

service purchase scale of enterprises, it evaluates the discount degree, and provides enterprises with premium and strict selection services.

Through these practices, the risk of the transaction process is reduced, and the initial synergy between the seeker and the solver is achieved.

● *Tactical synergistic effect:*

In the process of important tasks (such as collaborative challenge mode), a strict anonymity system is implemented between seekers and solvers. Due to the considerations of trade secret disclosure and unfair competition, the two parties are unable to communicate before the solution is approved, which lead to a decline in task performance. In order to balance efficiency and confidentiality, the platform allows seekers who publish important tasks and certain solvers to apply for a communication "channel" through which the two parties can fully communicate on the whole progress although remains anonymous. By doing so, on the one hand, solvers have greatly increased their confidence due to the full attention from the seeker. On the other hand, seekers can directly understand the current stage and quality of the task, which not only eliminates schedule concerns, but also facilitates the review from the perspective of process and result and increases the accuracy of the solution's appraisal. Through the above methods, the potentials of seekers and solvers can be stimulated without leaking important secrets, and tactical synergy is achieved to an extent.

● *Strategic synergistic effect:*

With the improvement of various rules and regulations on the platform, the number of solvers continues to grow. However, it is found that there were a lot of supply-demand asymmetry problems in the early stage of the platform. The main problems are:

- It was difficult for a large number of solvers to receive orders that were suitable for them.

- The demand satisfaction rate of seekers was low.

The reasons for the above scenario mostly lay in the inconsistent understanding of each other and the high uncertainty of non-standardised services. Hence, the platform launched a unique matching system. On the one hand, using the resources and capabilities of the platform to professionally manage and train solvers, such as the "Wangpu" service[29]. It is a complete set of operation tools provided to service providers (both seekers and solvers) to help them maximise their attractiveness and improve the conversion rate of service. On the other hand, Witmap offers guidance to solvers to find orders that match their capabilities, and also helps seekers with scarce resources to find suitable solvers to reach cooperation.

Based on the above, the synergistic incentive effect between seekers and solvers on the platform is summarised in Figure 6- 9.

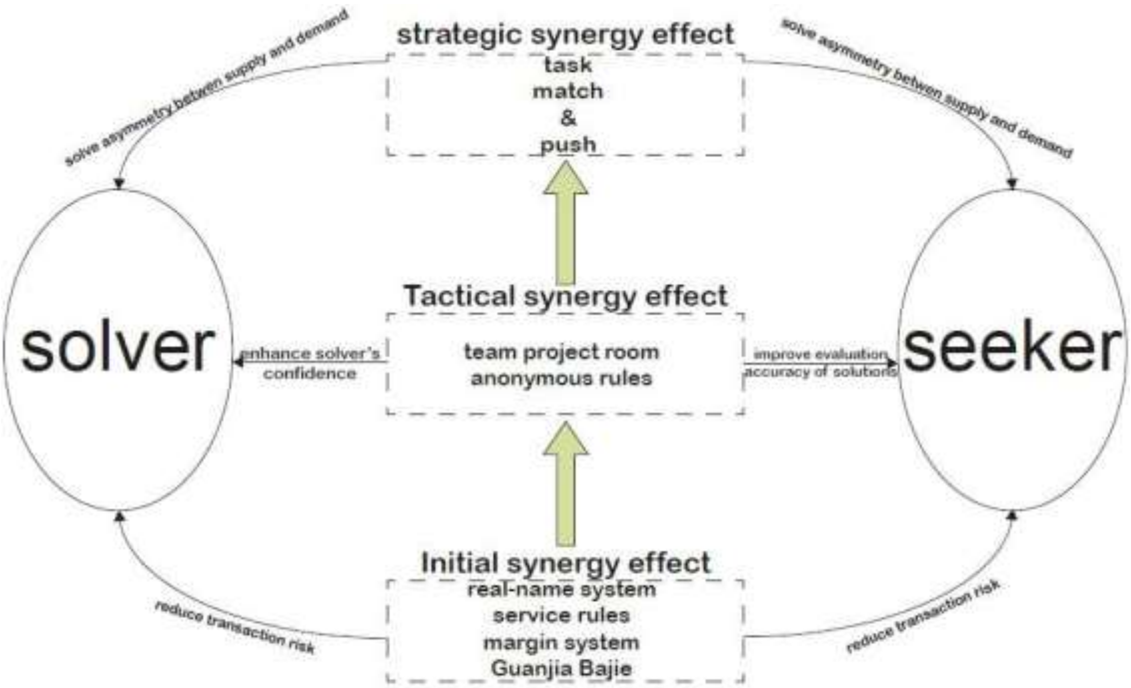

Figure 6- 9 The synergistic incentive effect between seekers and solvers

(abstracted by the author)

29 https://www.zbj.com/wangpu/index

From Figure 6- 9, the platform has formed three levels of synergistic incentive effects:

- The first level (low level) is the initial synergistic effect, which is derived from the implementation of services and systems such as real-name system, service rules, margin system and Guanjia Bajie (online task combing and diagnosis, match of service resources, and full project supervision). It reduces transaction risk between seekers and solvers.

- The second level (medium level) is the tactical synergistic effect. Benefited from the application of team project room and anonymous rules, it strengthens the confidence of solvers and improves the accuracy of the evaluation of the task solution by seekers.

- The third level (high level) is the strategic synergy effect. Through task matching and accurate pushing mechanism, the problem of asymmetry in supply and demand between seekers and solvers is solved.

The three-level synergistic incentive effect covers the overall process of crowdsourcing contest tasks, which is conducive to improving the overall efficiency of SMEs CCI.

<u>Synergistic incentive effect among solvers</u>

The synergistic incentive effect among solvers are most clearly reflected in the collaborative challenge tasks. It is difficult for a single solver to complete the task in a short time, and the most satisfactory solution comes from the teamwork. The synergistic incentive effect among solvers is analysed below.

● *Team building:*

The platform implements the team leader responsibility system in the collaborative challenge tasks. The leader can select solvers from the talent pool on the platform and form a task team to bid for the task. Simultaneously, the leader deconstructs and assigns the task module.

● *Task solving:*

In the process of solving tasks, the team can realise collaboration by forming a "team task room" which includes Web 2.0 style communities, discussion groups, information exchange functions and joint authoring tools, IM communication tools. Team members can use these tools for full knowledge sharing and communication to complete their respective task modules. The team leader will then achieve the integration of each task module. This both decentralised and centralised work method not only improves the efficiency of task solution, but also expands contacts and meets talents in many different fields, which helps to the solvers' future career development.

● *Distribution of the reward:*

One way to distribute the team reward among all team members is even allocation, and another more general one is that the team leader distributes according to members' performance contributions, which increases the innovation enthusiasm of members. In addition, only when members complete all the parts specified in the task, can they be rewarded. This fully promotes collaboration among team members, improves task performance, caters to the expected output of the seeker to the team, and enhances the confidence and enthusiasm of the seeker to increase rewards.

6.5.3 Uncertainty in the Effectiveness of Reputation Incentives

This part is going to verify the effectiveness of the reputation incentive mechanism. According to the principle of universality, first of all, web crawler is used to crawl the information of the solvers in the four industries of brand design, copywriting planning, marketing promotion and e-commerce service from Zbj.com, including solver's ID number, name, location, store opening years, business scope and so on. Services for SMEs CCI tasks from these four industries are the best sellers on the platform[30]. Second, according to the principle of timeliness, the transaction data of each solver in the last trading quarter (April, May, and June 2020) is collected according to their ID number,

[30] https://www.zbj.com/channel/guarantee?fr=qf.zbj.sy.jx

including precise transaction amount (i.e. task reward amount), net income, number of orders, number of favourable comments, favourable rate, comment label of each transaction, etc. Finally, the transaction tracking method is used to track the changes in the reputation level of the last transaction quarter (April, May, and June 2020), and the weighted average of reputation is calculated by taking the precise transaction amount as the weight, which represents the reputation level of the solver during the transaction period. After removing the duplicate data, a total of 296 pieces of data were obtained. According to the service provider's rating rules stipulated by the platform margin system[31], all data are divided into three groups according to the service provider reputation level: level 0-8 (low level), level 9-27 (medium level) and level 28-81 (high level). In each group, the three most important service income indicators - precise transaction amount, net income, and number of orders, are respectively analysed for their correlation with the reputation level. The results are shown in Table 6-6.

Table 6-6 Analysis on the effectiveness of reputation incentive

Item	Precise transaction amount			Number of orders			Net income		
Reputation level	0-8	9-27	28-81	0-8	9-27	28-81	0-8	9-27	28-81
Sample number	72	163	61	72	163	61	72	163	61
Correlation coefficient	0.433	0.86	0.295	0.236	0.254	0.264	-0.124	0.392	0.199
Sig. (2-tailed)	0.000	0.000	0.021	0.046*	0.001**	0.039*	0.298	0.000**	0.124

Note: *. Correlation is significant at the 0.1 level (2-tailed). **. Correlation is significant at the 0.05 level (2-tailed).

According to the results of the correlation analysis, the reputation effectiveness is discussed as follows:

[31] https://quan.zbj.com/thread-6644-1-2.html

● Each income item of the solver does not always increase with the improvement of reputation level. The correlation coefficient and significance are adjusted by the level range, and there are certain differences in the effects of explicit indicators (number of orders, precise transaction amount) and implicit indicators (net income).

● In the low reputation level range (Level 0-8), the number of orders and precise transaction amount show a significant upward trend with the improvement of reputation level, but the relationship between net income and reputation level is not obvious (significance is 0.298), and they are negatively correlated (the correlation coefficient is -0.124). This shows that the level of solvers in the low-level range is not necessarily a reflection of their true reputation level. Solvers are easy to upgrade their reputation levels by click farm, so seekers are cautious about the identification of solvers' reputation levels. At the same time, due to the cost of click farm and tasks with features of simplicity and small reward amount, so although the number of orders received and the transaction amount increased with the improvement of reputation level, it did not actually increase the economic benefits of low-leveled solvers.

● In the medium range (Level 9-27), the number of orders, precise transaction amount, and the net income all have a strong positive correlation with the reputation of the solver. This shows that it is no longer easy to have click farm in this reputation range. Each level of reputation improvement takes more time and energy than the low reputation stage. Reputation improvement must truly be based on solver's service quality. Therefore, the marginal effect of reputation level is enhanced, and the solvers' ability, quality and credit level the reputation level represents are fully recognised by seekers, and it also shows a higher degree of discrimination. In addition, the effectiveness of reputation is most significant in the medium-level range, and efforts to maintain and improve reputation levels can bring obvious economic benefits to the solvers.

● In the high reputation level range (Level 28-81), the correlation between various income indicators and reputation level begins to decrease, and even the net income level and reputation level are no longer relevant. The reason is that the solvers already have a clear reputation advantage at this time, and common crowdsourcing tasks have been difficult to attract their interest. Bidding tasks and collaborative challenge tasks with high reward amounts are their goals. In this seller's market, solvers will naturally increase service pricing, and seekers will select the solver based on specific needs (such as industry attributes and process requirements). In addition, the high reputation level of the solver represents a certain degree of protection of rights and interests and can complete the crowdsourcing task with quality and quantity. Under this circumstance, reputation level no longer seems so important, and the marginal effect of reputation incentives has been weakened.

6.6 Analysis of the Defects of the Incentive Mechanism

From the above analysis, it can be seen that the platform has realised certain effectiveness of explicit incentives, implicit incentives, synergistic incentives and reputation incentives. However, the incentive mechanism still has the following defects:

● <u>The attractiveness of the pricing mechanism is not very prominent.</u>

The price of the task is determined unilaterally by seekers, the platform does not participate in its pricing process, nor does it provide any guidance on price setting. Most seekers on the platform are SMEs, and their main purpose of using crowdsourcing is to save innovation costs. Therefore, the price of tasks is generally low, which is not good for attracting solvers and achieving high quality solutions.

The price setting is still a fixed mode, and once set, it cannot be changed before the end of the task. No matter how many efforts solvers put in and how good the quality of the solutions is, solvers cannot gain more than the pre-set reward. Therefore, the performance incentives have not been effectively implemented, which restrict the motivation of solvers to participate.

How the reward is distributed among members under the team collaboration is entirely determined by the team leader. For the sake of fairness, some leaders adopt an even distribution method. This also increases the risk of opportunism and reduces solvers' enthusiasm for innovation.

● The reputation evaluation mechanism is not perfect.

Solvers' reputation based on growth value and credit points combines their current interests together with their future income, which plays an important incentive role. The core in the reputation incentive mechanism is to evaluate the solvers' reputation. The reputation evaluation mainly depends on three aspects: review (favourable, neutral, unfavourable), transaction amount, and violation penalties.

There is the possibility of information distortion:

- Reputation evaluation does not consider the time dimension. Whenever the evaluation is made, the reputation will be the same. In fact, the solvers' recent performance can best reflect their current reputation. Also, regardless of the time dimension, it is obviously unfair to the new solvers because they need a period of time to adapt to the rules. Perhaps the unintended violations at the beginning will seriously affect their reputation points, but this does not reflect their true reputation.

- The reputation system did not analyse the content of the evaluation information. As long as it is a "favourable" review, solvers will get a full reputation score. In fact, the specific content of the review can reflect the true attitude of seekers. At the same time, because the evaluation does need an extra cost, the mechanism cannot eliminate the phenomenon of click farm.

- The existing reputation mechanism stipulates that only when the transaction is completed can seekers evaluate and comment, and then update the reputation points of solvers. This makes it impossible for seekers who suspend the task due to serious dissatisfaction with solvers to comment and express their true feelings. That is why for most transactions that are normally completed, the satisfaction level of seekers generally is not low. Therefore, the existing reputation system has a “false prosperity” phenomenon.

● The knowledge sharing incentive needs to be further deepened and developed.

In the collaborative challenge tasks, team members communicate with each other in order to complete the task. By providing the “team task room” function, it increases the possibility of knowledge sharing and collaborative work among solvers and reduces the cost of task solution. However, this knowledge sharing incentive has not been promoted in all tasks. Quan.zbj.com is a community for ordinary solvers to learn and communicate, but most of the knowledge shared on it is mainly introductions to operations and interpretation of general rules. Few advanced solvers share success stories and professional knowledge of themselves. The root cause is that they are worried about knowledge leakage and cannot get attractive rewards.

● The quality evaluation and selection process of the solution is not transparent enough.

In the reward contest mode, the role of monetary incentive is undoubted that only the winning solver can get the reward. Therefore, the quality evaluation of the submitted solution and the process of selecting the best solution are particularly important especially in high-value tasks. In addition, the evaluation process should be highly transparent to eliminate the solvers’ concerns about violation. However, on the platform, although the quality standards are determined when the task is issued, the decision-making right of the winning solution is almost concentrated in seekers, and the platform only conducts a general review of the winning solution. However, it is difficult to find answers to questions such as who will evaluate the solution, how to score it, and whether there is cheating. This leads to the solvers’ credit risk perception and unfairness perception, which reduces their enthusiasm for participation.

6.7 Safeguard Measures for the Incentive Mechanism

In response to the questions of the incentive mechanism summarised in the previous section, this section puts forward some guaranteeing measures to promote the effectiveness of the incentive mechanism of the SMEs CCI.

Optimisation of the pricing mechanism

The platform should help seekers to properly review and evaluate the workload of tasks and provide pricing guidance services to seekers, so as to eliminate the phenomenon of invalid tasks caused by unreasonable prices.

Dynamic pricing methods should be adopted to formulate the quantitative standard of solution quality evaluation and unit performance reward standard, and the task price according to the quality submitted can be dynamically adjusted.

The platform can consider establishing an upgraded version of customer service system to distinguish high-end tasks from ordinary tasks. The qualification of the high-end task seekers shall be accurately reviewed, and the minimum task price shall be set while the identity of solvers participating in it shall also be limited. This differentiated pricing method is a good way to avoid eliminating low quality solutions.

Refinement of task allocation and segmentation services

The crowdsourcing task itself has a certain incentive effect, but it must be based on the matching of tasks and solvers' capabilities. Although the existing matching mechanism offered by the platform solves the problem of idle resources, it still basically adopts the principle of random matching in task matching. If tasks with low skill requirements are assigned to high-capacity solvers, it will result in low efficiency. Therefore, the platform should further refine the task allocation system to help solvers find suitable tasks among a bewildering variety of tasks especially in collaborative challenging mode, or precisely push the task to the most suitable solver through certain methods, which can generate great incentive effects for both seekers and solvers. An evaluation system for tasks to be assigned based on important dimensions such as task complexity, quality and importance can be established, and reasonable dimension weights can be set to calculate the “core degree” that can reflect the skill level required for the tasks. Also, reasonable estimation is made for all idle solvers according to their interest degree, and capacity level, experience value to solve such problems, and the comprehensive capacity index of each solver is calculated. Then, the tasks and the solvers are ranked according to the “core degree” and “comprehensive ability” respectively and pushing matching tasks according to the ranking.

Improvement of supervision system and reward and penalty system

The existing real-name system, credit score system and service rules of the platform have largely guaranteed the standardisation of the transaction process, but behaviours such as credit clip farm, solution plagiarism, and malicious crowdsourcing significantly reduce the role of the incentive mechanism can’t be completely eliminated yet. Therefore, the platform should further improve the process supervision system and reward and penalty system. For example, for the solutions submitted by all solvers in the pitch mode, a standard re-check system can be used. Once the set repetition rate is exceeded, it is considered as plagiarism, and the solver is disqualified from the transaction for a long period of time. Establishing a public monitoring platform for malicious acts, and actively encouraging all platform users to report malicious acts. The direct monetary awards or reputation points should be increased for solvers who are active and skilled in their work, and penalties for violations of transaction norms all also be intensified, thereby regulating the order of the platform and promoting the continuous and stable development of crowdsourcing innovation.

Improvement of the reputation incentive

Reputation incentive not only satisfies the internal motivations of solvers, such as the sense of accomplishment and social value, but also are usually related to their economic benefits. In view of the shortcomings of the reputation evaluation mechanism (grade rating system), it is believed that it can be improved from the following aspects:

- Considering the time dimension in the evaluation of reputation. The recent evaluation can be intercepted to dynamically update the solvers' reputation value so as to ensure that the reputation value more reflects the recent behaviour of solvers.

- In the assessment of reputation, it is not only based on the rating of the evaluation (such as favourable, neutral, unfavourable), but also on the information of the reviews. In particular, it is necessary to extract the sentiment words in each review (for example, “satisfaction”, “very”, “haha”, “expensive”), and assess solvers' reputation based on the tone and frequency of sentiment words to ensure the accuracy of reputation to the greatest extent.

- Broadening the scope of evaluation and allowing transactions that are interrupted accidentally to be evaluated as well. The content of the mutual evaluation by seekers and solvers is also included in the reputation system.

<u>*Diversification and transparency of the evaluation and selection process of the solution*</u>

The evaluation subject should be more diversified. The platform itself should be dedicated to building an expert pool which also includes the Internet public and even solvers. Hence, a three-dimensional evaluation mechanism consisting of enterprise experts, platform experts, and Internet users should be built up. Especially for tasks that require perceptual evaluation, such as creative tasks, grassroots platform users may have a more unique vision than experts. And letting solvers participate in the evaluation can produce a greater incentive. Also, the evaluation criteria/standards should not only be a simple description but should be gradually quantified to improve the objectivity and conviction of the solution selection.

6.8 Conclusions

This chapter verifies the effectiveness of the incentive mechanism of a typical

SMEs crowdsourcing contest platform (Zbj.com). It is found that the explicit and implicit effects of the incentives of crowdsourcing contest platforms are equally important. The initial synergy, tactical synergy and strategic synergy between seekers and solvers have been basically realised. However, the effectiveness of reputation incentive remains uncertain. Moreover, based on the research findings, crowdsourcing contest platforms still face challenges in pricing mechanism, reputation evaluation, knowledge sharing incentive mechanism and solution evaluation selection. At last, from the aspects of optimising pricing services, refining task allocation and segmentation, perfecting supervision and reward and penalty systems, improving reputation mechanisms, and evaluating and diversifying the selection process of the schemes, the guarantee measures for the realisation of the incentive mechanism of the crowdsourcing platform for SMEs are proposed.

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7 DISCUSSION

Based on the research findings of the whole thesis, this chapter gives detailed answers to the three main scientific questions proposed in Chapter 1 and discusses the possible impact of the research findings on real SMEs crowdsourcing practices. And the limitations of this thesis and the refining solutions are also given out at the end of this session.

7.1 Answers of the Main Research Questions and Practical Implementations

Research Question 1: What are the motivational factors that influence solvers to participate in SMEs crowdsourcing contest innovation?

This question is the precondition of the incentive mechanism design and social exchange theory is chosen as the theoretical basis of this research. The motivation factors that affect solvers' participation in SMEs *crowdsourcing contest innovation* (CCI) are divided into two categories: benefit perception (positive) factors and cost perception (negative) factors.

Key findings:

- Material motivation (path coefficient is 0.205) is an important factor that affects the benefit perception of the solvers, but not the main factor.

- The path coefficients and significance of the two non-material motivation factors - 'knowledge acquisition and sharing' and 'reputation' (path coefficients are 0.256 and 0.504 respectively) are higher than material motivation.

- The role of social belonging factor (path coefficient is 0.098) is not significant (path coefficient is 0.098).

Discussion: The rewards in SMEs CCI tasks are generally not high, but why are the solvers still keen on it? This is closely related to the low requirements for knowledge and skills, and the low entry threshold of SMEs innovation tasks. However, it cannot be ignored that the non-material motivation of solvers is also an important factor in promoting solvers' continuous participation. Solvers participating in SMEs CCI tasks hope to acquire certain knowledge and skills from the process of problem solving or share experiences with others through the platform. At the same time, the new solvers hope to solve the problems with high performance, in order to accumulate a certain reputation on the platform and lay the foundation for winning more crowdsourcing innovation tasks in the future. Therefore, although many scholars (Boudreau and Lakhani, 2009; Acar, 2018; Wang and Yu, 2020) find that material rewards are the most direct and most important motivational factor, it is believed that the finding is not entirely suitable for SMEs CCI. As a result, it is not only necessary for CCI platform to increase the task reward amount, but also important to increase the skill training for solvers and reduce the technical threshold for solvers to acquire and share knowledge. In addition, it is vital to establish a dynamic reputation incentive mechanism based on the point grade system and increase the winning probability of solvers with high reputation levels in SMEs CCI.

Key findings:

● The task complexity has no significant effect on the cost perception of the solvers in SMEs CCI (path coefficient is 0.072).

● Intellectual property risk and waste of resource will significantly increase the cost perception of the solvers (path coefficients are 0.309 and 0.621, respectively).

Discussion: In view of the characteristics of SMEs, the complexity (difficulty) of CCI tasks from SMEs is generally lower than that of large enterprises. Although the task complexity means that the probability of failure, it does not necessarily enhance the solvers' cost perception for the feeling of self-recognition. This is different from the research conclusions of Zhu, Zhang and Zhang (2016) who believed that the complexity of the task will weaken the influence of solvers' internal and external motivations on participation willingness to a certain extent, but it is consistent with research findings of Sun *et al.* (2015) in some respects who pointed out the complexity of the task will negatively regulate its influence on the solvers' extrinsic motivation. In this thesis, the real cost perception factors are: the weak awareness of property rights of SMEs, and problems in the best solution selection and privacy protection, as well as the asymmetry of information and the risk of resource waste caused by the "winner-takes-all" mechanism (Qiao, 2017). Therefore, first, for designers of the incentive mechanism, differentiated rewards should be set according to the complexity of task, instead of the winner-takes-all mode, multi-winning reward mode could be considered. Second, encouraging solvers with strong professional skills to participate in the form of a "team", giving full play to the role of target incentives. These could be considered as effective measures to reduce the risk of resource waste. At the same time, effective results protection mechanism should be adopted to reduce intellectual property risks.

Research Question 2: How do SMEs (or crowdsourcing platforms) design attractive incentive mechanisms according to the motivation factors of solvers?

According to the significant benefit perception factors, based on the principal-agent model, the incentive mechanisms of material, reputation and knowledge sharing are designed respectively, and the cost factors in the mechanism design are also considered. It is believed that the design of incentive mechanisms should be based on the "performance" of the tasks: the higher the quality of the solution, the greater the reward. The key findings and the discussion of their effectiveness (performance and economic benefits) are shown below.

Key findings:

- For SMEs CCI tasks that can be modularised or involve more complex technical issues, multiple solvers can be recruited to collaborate as a team on the platform with a good interactive atmosphere, and the appropriate material incentive mechanism should be adopted.

Discussion: When the SMEs CCI task is complicated, it is recommended to solve the task in the form of team collaboration. This is consistent with the research of Rajala *et al.* (2013) and Wang (2020). In this scenario, seekers can use the material incentive mechanism (TR) that combines team performance rewards and individual performance rewards. That is, the reward is not only positively related to solvers own performance, but also positively related to the team performance, so as to enhance the altruistic efforts among team members. Under the TR incentive mechanism, highly complex tasks can produce more obvious incentive performance for teamwork represented by high-self-interested efforts (Shi, Lin and Tang, 2014). At this time, solvers' self-interested efforts, altruistic efforts, and task performance are negatively related to the integration characteristics among modules and negatively related to the number of solvers. Obviously, collaboration among members will completely disappear under NR mode (rewards only based on individual performance). Furthermore, it is worth noting that although the task risk will increase the reward cost but reduce the economic benefits of the seekers, it is still recommended that the seekers adopt the TR model. Because the high performance produced by collaborative (altruistic) efforts will offset the expenditure of team performance reward expenditures. However, in general, the risk aversion psychology of solvers will reduce the crowdsourcing performance and economic benefit of seekers.

Practical Implementations: Collaborative effort can only be boosted under a reward model based on total team performance. Therefore, for SMEs or crowdsourcing contest platform:

It is suggested to improve the existing "pricing" and "evaluation" mechanism for complex SMEs CCI tasks. The reward amount cannot be fixed before the task is implemented, but should be determined based on the quality (performance) of the submitted solutions.

When the retained task amount is high, the collaborate team should be committed to the completion of tasks, rather than focusing on the maximisation of economic benefits. At the same time, the seeker should use the method of target incentive combined with material incentive to achieve the maximum effect.

For leaders, in the process of recruiting team members, on the one hand, it is necessary to absorb the reasonable number of members with higher knowledge and skills; on the other hand, it is more important to understand the risk preferences of members. Only when the members' risk aversion is low, it is economical to set up the team. Otherwise, the expected task risk will reduce members' collaborative/altruistic efforts. Therefore, it is necessary to conduct a risk appetite test by the team leader when recruiting members. To be specific, the team leader can analyse the risk appetite and degree of selfishness of solvers through questionnaire surveys and scenario experiments. According to the test results, the overly conservative and selfish solvers are excluded in order to build a crowdsourcing team with effective communication, mutual assistance and collaboration among members.

Key findings:

- If there are certain correlations among the tasks released by one SME, it is advisable to design a multi-period dynamic performance incentive mechanism based on dual reputation effects. This is also in line with the reputation motivation of solvers.

Discussion: Under the explicit reputation incentive mechanism, seekers estimate solvers' expected performance based on their performance in the previous task which is continuously adjusted dynamically in each task cycle. The level of implicit reputation determines the degree of cost reduction of solvers' innovation efforts. It is believed that reputation incentives will be more effective when fixed rewards are simultaneously implemented for all solvers by changing unit performance reward or fixed reward, result in higher economic benefit of the second task stage.

However, the dynamic reputation incentive mechanism will have an inevitable negative effect - the ratchet effect. It is thought that an important way to reduce the ratchet effect is to attract more solvers to participate in the task. By expanding the task scale, the solvers' retained effort will be decreased because of the competition pressure brought by other solvers. It is also believed that the ratchet effect is not necessarily a negative effect, because it provides a basis for seekers to save incentive cost.

Compared with the non-reputation incentive mechanism, the reputation incentive mechanism can theoretically improve the performance of CCI the second task stage, while incentive cost of the seekers is indeed reduced. In addition, when the explicit reputation correction coefficient (i.e., reputation uncertainty) is low and the implicit reputation coefficient is high, the task performance level in the first task stage can be and the Pareto improvement of the utility of both the seekers and the solvers in the two stages can be realised.

Practical Implementations:

> For seekers, it is necessary to enhance the effectiveness of reputation incentives by improving the solvers' winning probability, promoting outstanding successful cases, and offering direct material rewards to solvers. What's more, when attracting solvers to join, the efforts in screening of solvers' knowledge, skills, experience, word of mouth should be strengthened. It is also suggested that a comprehensive dynamic evaluation of the solvers' performance in each task should be carried out, and the reputation points of theirs should be dynamically updated based on the evaluation results. Most important of all, the evaluation mechanism must be consisted of enterprise experts, platform experts and network users, and consider the influence of time dimension. By doing so, the objectivity of the evaluation criteria and the transparency of the evaluation process will be continuously improved, thereby the uncertainty of explicit reputation can be reduced.
>
> In the implementation of reputation incentives, all solvers should be considered to give a certain fixed reward. However, the winning bonus of the task should not be immobilised, and the performance reward system should also be implemented. Furthermore, the CCI platform

should provide solvers with free skill training, comprehensively promote the improvement of their service skills, so as to improve the conversion coefficient of innovation effort performance and the implicit reputation coefficient at the same time.

The increase in the number of solvers helps reduce the ratcheting effect of reputation incentives. Therefore, lowering the barriers to entry, increasing task rewards, and attracting more solvers are important guarantees for the successful implementation of the reputation incentive mechanism.

Key findings:

● Even if there is no extrinsic incentive, the solvers are willing to invest in knowledge sharing efforts. The main reason is that, according to the research findings of Chapter 2, waste of resources is one of the main factors that inhibit the willingness of solvers to participate SMEs CCI. Therefore, solvers are willing to actively contribute knowledge sharing efforts to improve their task solving ability, so as to increase the winning probability and reduce the risk of wasting resources.

● The knowledge sharing incentive mechanism will certainly improve the performance of CCI while achieving a win-win situation for the economic benefits of both the seekers and solvers, and fairness concern of solvers has a certain impact on incentive effect.

Discussion: Knowledge sharing can both help improve solvers' problem-solving skills and reduce the cost of solution effort. However, in SMEs CCI, it is not easy to realise knowledge sharing behaviour, especially when the solvers have the psychological characteristics of fairness concern (Shi, Lin and Tang, 2015). The research findings obtained from the theoretical model indicate that solvers have the willingness to share knowledge, even in the absence of external incentives. But the establishment of the theoretical model is based on strict assumptions. In the incentive model, the assumption that all solvers are rational men is somewhat different from the actual situation. The feature/restriction of the small amount of awards of SMEs CCI tasks makes the solvers' fairness concern have a greater impact on their behaviour. The fairness concern of solvers can increase their sense of jealousy. And the willingness to share knowledge in favor of other solvers' interests certainly decreases because of the sense of jealousy, while the self-interest effort obviously increases. But fairness concern must be able to highlight the relative value of the knowledge sharing incentive mechanism for both the seekers and solvers. Because the higher the sensitivity of the fairness concern, the higher the degree of incentives rewards should be invested by seekers, and then the more frequent knowledge sharing behaviours are stimulated. This finding expands the scope of application of the fairness concern theory.

Practical Implementations:

Crowdsourcing organisers (seekers and/or platforms) should actively promote the knowledge sharing incentive mechanism in the crowdsourcing community. A knowledge sharing community (such as a forum) can allow participants (seekers and/or solvers) to freely exchange their professional knowledge and skills. In addition, a reasonable sharing behaviour evaluation system should be established to effectively identify the part of the shared knowledge that can truly improve skills as a reward benchmark, rather than simply considering the frequency of sharing behaviour.

Crowdsourcing organisers should carefully treat solver's fairness concern and better transform it into "pride" rather than "jealousy". On the one hand, more attention should be paid to the cost assessment related to the solvers' experience or skill level, highlighting the role of knowledge sharing in reducing the cost of private effort, so as to increase the "implicit effect" of knowledge sharing behaviour. On the other hand, strengthen the implementation of the knowledge training system in the crowdsourcing community and improve the ability to transform shared knowledge into crowdsourcing performance. Based on this, the crowdsourcing organisers should increase the task bonus to attract more solvers and effectively expand the scale of the competition.

Considering the impact of fairness concern on solvers' behaviour, it is suggested that the crowdsourcing organisers should give solvers a test of their psychological characteristics. If the solvers are too jealous or conservative, they should be excluded from the task. In addition, during the implementation of the task, the organisers should also maintain certain communication with solvers in order to guide them not to pay too much attention to the income difference between themselves and other solvers.

Research Question 3: How effective are the incentive mechanisms in the current crowdsourcing practice?

By analysing the incentive mechanism of SMEs CCI in practice, the effectiveness of the theoretical incentive mechanism designed in this thesis is discussed.

Key findings:

- Monetary reward is currently the most important material incentive method in crowdsourcing practices.

Discussion: The reward contest mode and the bidding mode on the platform reflect the "winner-takes-all" feature of crowdsourcing contest innovation. Compared with single people rewarding, the multi-people reward method is obviously more popular. The explicit effect of monetary rewards is obvious, but it is found that the clarity of the reward amount is more attractive to solvers than the amount for risk aversion. Moreover, solvers participating in high reward tasks are talents with high knowledge and skills and pay more attention to the hidden effects of tasks, such as training innovation ability, building career channels, finding career partners. In this scenario, solvers care much less about the monetary reward. These hidden effects are similar to the findings of

Goncalves *et al.* (2015) and Brabham (2010), verifying the importance of non-material elements in the motivation of participation in SMEs CCI.

Key findings:

- The collaborative "challenge" mode is an important manifestation of the synergistic effect of the incentive mechanism on the crowdsourcing platform.

Discussion: Collaborative "challenge" is a new contest mode which the reward amount is generally much higher than that of ordinary SMEs CCI tasks. Most tasks of this mode can be modularised and require the collaboration of multiple solvers with high knowledge and skills to form collaborative teams. However, in terms of the benefit distribution, the ideas of the TR mechanism and knowledge sharing incentive mechanism are not fully implemented. This is because, on the one hand, the fixed reward amount system is still being adopted on the platform, and the reward amount is determined when the task is issued and cannot be adjusted according to the actual task performance. On the other hand, the distribution of benefits of each team member is entirely carried out by the team leader, and it is impossible to do the "secondary distribution" of reward based on the total contribution of the team. The secondary distribution of reward means after the first allocation that the team leader allocates a certain amount of rewards to all the solvers, the remaining reward is distributed according to the degree of contribution of solvers to team total performance, which can be regarded as a kind of performance reward. Therefore, the establishment of a diversified and transparent evaluation mechanism, as well as a special knowledge exchange area to promote the integration of knowledge and skills in different fields, is an important element of guarantee system for SMEs CCI.

Key findings:

- Reputation incentive has been adopted in practice, but the effectiveness of it remains uncertain.

Discussion: Reputation incentives have already achieved certain outcomes on crowdsourcing platforms. However, it is found they have certain flaws. The problem is that, first, there is the possibility of information distortion in reputation evaluation and the general review - positive, moderate and negative cannot fully reflect the true feelings of the seekers. Second, reputation grade does not consider the element of time, which is not only unfair to new solvers, but also fails to reflect the dynamic characteristics of reputation.

Therefore, a quantitative reputation evaluation model based on restraining the fraudulent behaviour of both the seekers and solvers should be established to improve the accuracy of reputation estimation (Hao *et al.*, 2014). Firstly, it is necessary to strengthen semantic analysis and consider the time dimension in the calculation of reputation points (Lu *et al.*, 2018). Secondly, the procedural supervision mechanism should be strengthened to prevent the behaviour of click farm.

7.2 Research Limitations and Possible Solutions

The limitations and their possible solutions of this thesis mainly include the following aspects:

● In the design process of the incentive mechanisms, this thesis considers the psychological characteristics of the solvers (such as risk aversion and fairness concern) and the constraints of the complexity of the tasks, but does not consider the financial constraints of the SMEs as the seekers in detail. For the performance incentive mechanism, the actual reward amount invested by the solver is closely related to the innovation efforts of the solver and the performance of the solution. Therefore, the innovation funding constraints of SMEs will have a comparatively important impact on the incentive performance. In future studies, the reward amount constraint can be added to the constraints of various incentive models, so as to make the research conclusion more consistent with the characteristics of SMEs.

● This thesis does not distinguish the types of tasks in the design of incentive mechanisms. Job characteristic theory, a theory of work design, points out that different types of tasks have significant differences in task complexity, autonomy, feedback, consistency, etc., which in turn significantly affect the motivation of task participation (Blanz, 2017). Tian, Deng and Fei (2016) also found that the main variables that determine task performance in crowdsourcing competitions for professional knowledge, creative, and experimental tasks are different. Creative tasks are affected by the subjective preferences of the seeker, while professional knowledge ones depend mainly on the knowledge of the solver. Therefore, the winning probability of the solvers in different types of SMEs CCI tasks is also different. As the importance of crowdsourcing innovation is recognised by more and more SMEs, the types of tasks posted on crowdsourcing platforms also tend to diversify, and participants exhibit different behavioural characteristics in various tasks. Therefore, designing a differentiated crowdsourcing contest incentive mechanism for different task types is of great significance to obtain high-quality solutions to the greatest extent.

● This thesis mainly theoretically conducts the design and performance analysis of incentive mechanisms for SMEs CCI, but these designed incentive mechanisms have not been fully applied in the operation of mainstream crowdsourcing platforms, especially the non-material incentive mechanisms. Therefore, how the actual performance of these incentive mechanisms needs to be further tested by practice. In addition, this thesis only constructs the incentive mechanisms considering two main non-material factors: reputation and knowledge sharing, which cannot completely cover the non-material motivation of the solvers. Motivations such as emotional communication and personal ability display could also have an impact on the innovative efforts of the solvers. Meanwhile, the solvers' efforts will be affected by the crowdsourcing platform environment (such as platform ease of use) as well. So, how to build a more systematic non-material incentive system of SMEs CCI to stimulate the internal motivation of the solvers and create a platform environment conducive to non-material incentive in practice are also important directions of this thesis.

● Due to the influence of geographical location and pandemic of COVID-19, face-to-face in-depth interviews with the seekers, solvers and platform itself could not be carried out, which to a certain extent affected the understanding of the effectiveness of the incentive mechanism of SMEs CCI. Even though online interview is an alternative method, due to time lag and other reasons, online interview cannot create the communication atmosphere of face-to-face interview, and it is not easy to capture the changes of the interviewees’ expressions in the first time so as to obtain more in-depth information. In addition, in the process of web crawling, the selection of keywords is subjective to some extent, and technical limitations cause the research results to be somewhat biased with the actual situation. Therefore, in the future, a comprehensive investigation with the seekers, solvers and staff of the platform in person will be conducted.

In summary, the limitations and challenges of this research mainly lie in how to make theoretical models as close to the reality as possible; how to quantify the task category and characteristics, the psychological factors of solvers into the theoretical model design. Besides, the validity and value of the theoretical models still needs to be fully tested in practice.

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8 CONCLUSIONS AND FUTURE WORK

8.1 Conclusions and Contributions of Knowledge

8.1.1 Conclusions and Answers to the Main Research Questions of the Thesis

The specific conclusions in relation to the original objectives are as follows:

Objective 1. To understand the motivational factors that affect solvers to participate in SMEs crowdsourcing contest innovation

- Among the benefit perception factors, material motivation is an important factor affecting solvers' participating willingness, but it is not the most important factor (Chapter 2).

- The path coefficient and significance of the two non-material factors - knowledge acquisition and sharing, and reputation, are higher than material motivation. Besides, social belonging does not significantly increase the solvers' perception of benefit (Chapter 2).

- Among the cost perception factors, there is uncertainty in the impact of the complexity of tasks on solvers' participating motives, while intellectual property risks and waste of resource have high path coefficients and significance for cost perception (Chapter 2).

- The continuous participation of solvers in SMEs crowdsourcing contest innovation (CCI) is determined by the net utility determined by benefit equivalent and cost equivalent. Meanwhile, it is also positively regulated by the ease of use of the crowdsourcing platform (Chapter 2).

Objective 2. To design incentive mechanisms of SMEs crowdsourcing contest innovation

Conclusions of the material incentive mechanism:

● When the task is complicated and can be modularised, solvers can participate SMEs CCI in the form of a team. Solvers in crowdsourcing teams have two kinds of efforts: self-interest effort and altruistic effort (Chapter 3).

● In TR mode (the material incentive mechanism based on the total performance output of the team), when the retained task volume is low, the self-interest and altruistic effort are positively related to the task cooperation effect, and negatively correlated with the solvers' risk preference; otherwise, the risk preference improves solvers' self-interest effort, but reduces their altruistic effort (Chapter 3).

● NR mode (the material incentive mechanism based on the solver's individual performance output) does not generate any altruistic efforts. As a result, its task performance is lower than that of TR mode, and solvers prefer TR mode from the perspective of economic benefit. However, this conclusion is only valid when the retained task volume is high. Otherwise, there are uncertainties between the task performance and the seeker's preference of incentive mechanisms (Chapter 3).

Conclusions of the reputation incentive mechanism:

● If the correlation among multiple crowdsourcing tasks from one seeker is strong, a two-stage dynamic incentive mechanism combining reputation and material rewards can be set up which needs to consider multi-stage incentive objectives and dynamic adjustment of reputation output (Chapter 4).

● The reputation incentive mechanism will generate a ratchet effect which weakens the task performance in Stage 1. However, the increase of solvers' number helps to reduce the ratchet effect (Chapter 4).

● The implementation of reputation incentive mechanism will definitely improve the innovation efforts and task performance in Stage 2. And only when the explicit reputation uncertainty is low and the implicit reputation coefficient is high enough, the innovation effort and task performance of Stage 1 will be higher than that without reputation incentives (Chapter 4).

Conclusions of the knowledge sharing incentive mechanism:

● Certain material incentives can be given according to the knowledge sharing behaviour of the solvers within the crowdsourcing community, which is conducive to reducing innovation costs and improving the performance of crowdsourcing tasks. But the knowledge sharing behaviour can not directly improve the solvers' winning probability in SMEs CCI (Chapter 5).

● The horizontal fairness concern of solvers can promote seekers to implement knowledge sharing incentives, improve the optimal unit knowledge sharing rewards, increase the solvers' private effort, but reduce the solvers' knowledge sharing effort (Chapter 5).

● The relationship of the task performance, the economic benefits of the seeker and the solvers' fairness concern depends on the ratio between the performance conversion rate of solvers' private effort and the performance conversion rate of solvers' knowledge sharing efforts (Chapter 5).

● Knowledge sharing incentive mechanism can achieve a win-win in terms of the economic benefits of both the seekers and solvers compared with no knowledge sharing incentives (Chapter 5).

Objective 3. To verify the effectiveness of the designed incentive mechanisms and give out guarantee measures

- Monetary incentive, reputation incentive, and knowledge sharing incentive have been applied on the crowdsourcing contest platform to a certain extent, showing an incentive effect that emphasizes the explicit, implicit, tactical and strategic synergy (Chapter 6).

- The effectiveness of monetary incentive is regulated by the amount of money, task type, and task complexity. The effectiveness of reputation incentive presented by the relationship between the solvers' reputation grade and their net rewards or orders is uncertain. Knowledge sharing incentives need to be further deepened and strengthened. Many new, lower-level solvers do not have a fast track to improving their skills (Chapter 6).

- It is necessary to refine the guarantee measures of the incentive mechanism from the aspects of optimising pricing services, refining task allocation and segmentation, perfecting the supervision, and evaluating and diversifying the solution selection process (Chapter 6).

Answers to the main research questions of the thesis:

Question (1): What are the motivational factors that influence the solvers to participate in SMEs CCI?

Both the benefit factors and cost factors can affect solvers' participating willingness in SMEs CCI. In this thesis, it is found that material, knowledge acquisition and sharing, reputation can encourage solvers to actively join in the crowdsourcing contest tasks published by SMEs. Meanwhile, intellectual property risk and waste of resources suppress solvers' enthusiasm for undertaking the SMEs CCI tasks. In SMEs CCI, considering task features such as winner-takes-all, low entry threshold and limited reward amount, to avoid the waste of resources including time and energy, the solvers tend to be risk adverse.

Question (2): How can SMEs (or crowdsourcing platforms) design attractive incentive mechanisms for the different motivational factors of the solvers, so as to maximise the economic benefits of the solvers and optimise the performance of the innovative task of the seekers?

It is suggested to design different types of incentive mechanisms according to various solvers' motives. Non-material incentives such as reputation incentive and knowledge sharing incentive should be combine with material incentive. And the amount of the reward should be relied on the crowdsourcing performance.

Question (3): In practice, how effective are the incentive mechanisms of SMEs CCI?

The explicit effects (the effectiveness of cash/monetary rewards and the effectiveness of the task itself) and the implicit effects (the opportunities to enhance innovative ability, broaden the breadth of knowledge fields, build up career channels, and obtain collaborative partners) of the incentive mechanisms are both significant. However, as far as reputation incentives are concerned, their effectiveness needs to be improved because there is uncertainty about the relationship between reputation incentives and the economic benefits of the solvers.

8.1.2 Practical Implementations of Designed Incentive Mechanisms

● Because the innovation effort of solvers is affected by their psychological characteristics, such as risk preference, fairness concern and so on. When Internet users do the registration to be a solver, the platform should set up a personality test. By doing so, it helps to push most suitable solvers to tasks based on task requirement.

● Different incentive mechanisms should be adopted according to different task features. For example, when the task is complex, it is recommended to separate the task into several modules and encourage solvers to form a team to join the crowdsourcing contest.

● Online community where solvers and seekers can share and get crowdsourcing contest techniques shall be built up. By doing so, solvers implicit reputation (higher skill level gained from crowdsourcing community) can be improved at certain extent which helps to reduce the incentive cost of SMEs. One thing which needs to pay attention to is the knowledge shared on the community should be filtered. Only the useful information such as personal skills in solving CCI tasks can be accepted, and satisfactory rewarded such as double points will be given to the one who offers this information. For the general information such as operating rules of the platform will be neglected and will not be rewarded.

8.1.3 Contributions of Knowledge

● By following the research sequence: determining research aim → setting up research objectives → choosing proper research methodologies, made a robust and academically rigorous research to support the view that crowdsourcing contest innovation offers an effective way of SMEs development

● Theoretically designed the material and non-material incentive mechanisms and examined their performance, verified their validation by publishing content strictly related journal papers

● Offered a general idea/framework of building up incentive mechanisms in SMEs CCI, the logical line is summarised in the following flow chart:

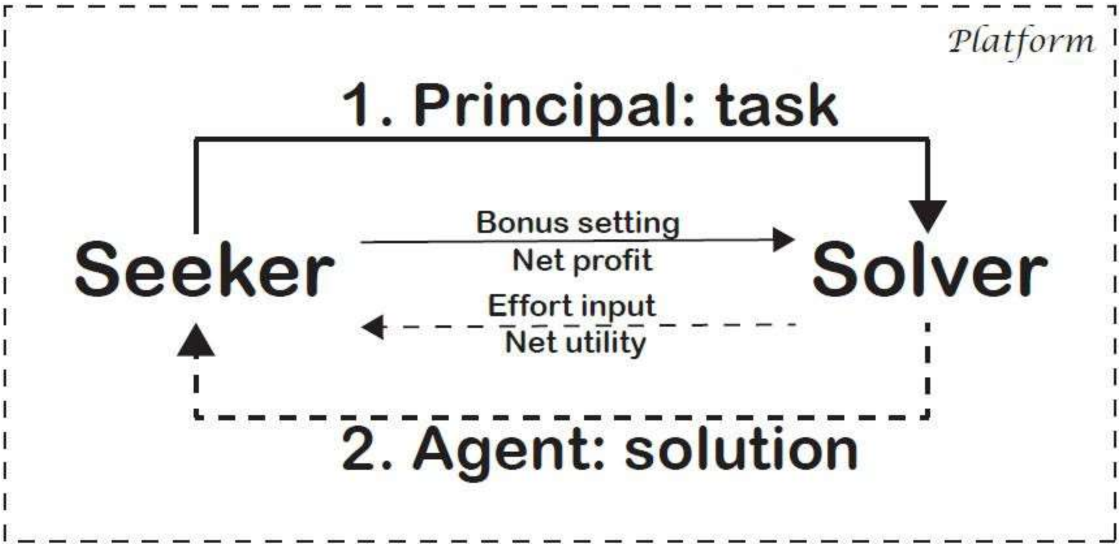


Figure 8- 1 Logics of building up incentive mechanisms of SMEs CCI

As shown in Figure 8- 1, seekers and solvers are in a principal-agent relationship where it exists on the online crowdsourcing contest platform. Seekers submit tasks and solvers offer solutions to the tasks. When building up theoretical incentive mechanisms in this thesis, the key is to know the decision variables of seekers and solvers. Seekers determine the amount of reward and their goal is to maximise the net profit. Solvers determine the input of their effort and their goal is to maximise the net utility in principal-agent relationship where the risk premium is unavoidable.

So according to the backward induction rule, firstly the solvers performance/output is decided based on their effort input and psychological variables; secondly the seeker's net profit is determined which equals the difference between the income brought by the solution offered by the winning solver and the cost which is the reward offered to the solvers; thirdly the model of the incentive mechanism is built up under the incentive compatibility constraints (IC) and individual rationality constraints (IR). The models in Chapter 3-5 are built up by following the above logics.

● Challenged the social exchange theory and the principal-agent theory to study the virtual network social relationships, expanded their application scope into information systems

● Verified the effectiveness of the crowdsourcing incentive mechanisms which has seldomly done in the related research area

● Proposed equations and built up mathematical models which may offer references for the relevant research in the future, the most valuable equations are listed below:

(1)

$$cE_i = a + \{3\left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji} \right) + yx_0 \sum_{i=1}^{N} \left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji} \right) - \frac{1}{2} k \left(e_i^2 + \sum_{j=1,j\neq i}^{N} E_{ij}^2 \right) - \frac{1}{2} pa^2 \left(\{3^2 + Ny^2 x_0^2 \right) \tag{3-5}$$

Equation (3- 5) is the deterministic equivalent return (i.e. economic benefit) of the solver in TR model (material incentive mechanism based on total team performance) in Chapter 3. The first three items of the equation are the fixed income a, the performance reward based on individual performance $\{3\left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji} \right)$, and the performance reward based on team total performance $yx_0 \sum_{i=1}^{N} \left(e_i + \sum_{j=1,j\neq i}^{N} E_{ji} \right)$. The fourth item is the total cost caused by solver's self-interested and altruistic efforts. And the last item is the risk negative utility.

(2)

$$P(e_{it}) = prob(m_{it} \geq max(m_{1t}, m_{2t}, ..., m_{nt})) = \frac{2^{n-1}(\ _t(k(e_{it} - e_{jt})))^{n-1}}{n} \tag{4-6}$$

Equation (4- 6) is one of the innovation points of this thesis. The deduction of the winning probability of solvers in SMEs CCI tasks strictly follows the model assumptions in Section 4.2, such as all the solvers are homogeneous.

(3)

$$U_i = \pi_i + \lambda_i \sum_{j=1,j\neq i}^{n} (\pi_i - \pi_j) \tag{5-1}$$

One of the challenges when building up mathematical models is to quantify psychological factors. Equation (5- 1) is the utility function of the solver under fairness concern. From the equation, the solver's utility is not only related to the solver's own profit, but the sum of his profit difference with other solvers. λ_i is the fairness concern coefficient and its value determines the final expected return (net utility) of the solver.

- Journal papers published and accepted by the community of researchers in crowdsourcing innovation, which are shown in Section 1.8

8.2 Future Work

Based on the research limitations of this thesis, the possible research directions in the future are listed below:

- How to optimise the incentive mechanism of SMEs crowdsourcing contest innovation

Through the combing of the existing research, it is found that although the relatively rich results have been achieved in the research of the design of the incentive mechanism for crowdsourcing competition innovation, the follow-up research is extremely lacking, that is, the exploration of the effectiveness of the incentive mechanism is rarely involved. This has led to the systematic and completeness of the research on the incentive mechanism of the SMEs CCI still need to be improved. In addition, in this thesis, the effectiveness of the incentive mechanism of mainstream platform of SMEs CCI was analysed by using descriptive analysis methods, and a true and objective description, analysis and evaluation of the incentive mechanism were made. However, in order to make the effectiveness analysis results closer to the practical situation, in future research, it is necessary to use decision-making analysis methods to analyse the effectiveness of the incentive mechanism from the perspective of the decision maker and propose a more reasonable incentive mechanism.

- How to extend the depth and breadth of validity verification of incentive mechanisms

Validity verification is an important link in the design and promotion of the incentive mechanisms of SMEs CCI. Because of the characteristics of the

Internet economy, a complete monopoly or oligopoly will be automatically formed within the same industry, Zbj.com is chosen as it has defeated its competitors and become the best online crowdsourcing contest platform in China. In the future, validity verification of incentive mechanism can be carried out on other representative platform outside China, such Amazon Mturk in the USA. comparative study can be conducted. The expansion of research objects and the conduction of comparative studies can help to summarise the overall framework of incentive mechanisms of SMEs CCI, thereby enhancing the generality of the research conclusions.

● How to deepen the research on crowdsourcing applications

It is necessary to deepen the application of social welfare crowdsourcing. For example, during the pandemic of COVID-19 that began in early 2020, many people have experienced the difficulty and high risk of having medical treatment. Although the NHS has launched an APP for online diagnosis and GP appointment, the service quality is not satisfying. It is worthy to establish a crowdsourcing platform to secure health care service anytime and anywhere. From the operational results of the NHS APP, the application of crowdsourcing in the medical field is still very challenging: 1) how to promote the crowdsourcing medical service; 2) how to encourage doctors and GPs to share their knowledge and resources; 3) how to improve the public confidence in the medical crowdsourcing platform.

● How to strengthen the research on mobile crowdsourcing

Under the trend of people’s increasing dependence on mobile terminals, the integration of crowdsourcing innovative platform services and mobile terminals is inevitable. And it is also found that the development speed of mobile crowdsourcing has exceeded the growth speed of Internet platforms. Therefore, the integration and competition of mobile crowdsourcing and corresponding crowdsourcing platforms, the protection of intellectual property rights on mobile crowdsourcing, and the quality of services of mobile crowdsourcing will become one of our future research focus points.

APPENDICES

Appendix A The Content of Questionnaire and Screenshots of Data Processing in Chapter 2

A.1 The Content of Questionnaire

This research is been undertaken by researchers in Cranfield University, on the topic of crowdsourcing innovation: crowdsourcing innovation refers to the practice of outsourcing innovative tasks to the online public through the Internet platform with the support of information technology (the Internet platform can be built by enterprises or a third-party intermediary platform; the online public can be professional or non-professional). Crowdsourcing innovation is the latest innovation model of open innovation, that has benefited by many companies, such as P&G, DELL, and IBM. The purpose of this questionnaire is to understand the universality of crowdsourcing innovation in business practice and provide support for further research on the general operating mechanism of crowdsourcing innovation.

This questionnaire will be used as part of an academic study, intended for publishing. However, we will ensure that any participant information will be kept anonymous. Your answers are of great value to our research. Thank you for your participation.

Part 1. Basic information

1. Your gender is:

A. Male B. Female

2. Your age is:

A. Under 20 years old B. 20-29 years old C. 30-39 years old D. 40-49 years old E. 50 years old and above

3. Your highest qualification is:

A. High school and below B. Associate degree C. Undergraduate D. Master's degree E. Doctoral degree

4. Your monthly income level is:

A. Below 3000 B. 3000-5000 C. 5000-10000 D. 10000-20000 E. Above 20000

5. How many times have you participated in the innovation tasks released by SMEs in the crowdsourcing community?

A. Never B. 1-5 times C. 5-10 times D. 10-20 times E. 20 times or more

6. Approximately how long did you participate in SME innovation tasks in the crowdsourcing community?

A. Within 6 months B. 6 months – 1 year C. 1 year to 1 and a half years D. 1 and a half years - 2 years E. Over 2 years

7. What types of SME innovation tasks do you participate in the crowdsourcing community (multiple choices are available)?

A. Creative type B. Planning type C. Product design type D. Marketing promotion type E. Programming type

8. Which platform do you visit most oftenly?

A. Zbj.com B. Amazon Mturk C. InnoCentive.com D. Other platforms

9. Your commonly used E-MAIL is:

Part 2. According to your completion of the SMEs *crowdsourcing contest innovation* (CCI) task, please answer the following questions. The answer to each question is a single choice among five options: "strongly disagree", "disagree", "general", "agree", and "strongly agree".

No.	Item	Strongly disagree	Disagree	General	Agree	Strongly agree
V10	Participating in the SMEs CCI provides you the opportunity to earn additional bonuses					
V11	Participating in the SMEs CCI provides you more part-time job opportunities					
V12	Participating in the SMEs CCI can gain knowledge and technology, which improves your problem-solving ability					
V13	On the CCI platform, you can share technical knowledge with everyone and promote progress together, which gives you a very sense of accomplishment					
V14	If your solution is selected, your reputation and popularity on the platform will be greatly improved					
V15	If your solution is selected, you can get points and level upgraded, the chance of winning the next project will be improved					
V16	Participating in the SMEs CCI can promote your future career development					
V17	Participating in the SMEs CCI can make friends and improve the sense of social belonging					
V18	Social identity and other emotional factors will promote your participation in the SMEs CCI					
V19	The SMEs CCI is relatively difficult and may not be completed by a single person. This will limit your motivation to participate					
V20	The description of the SMEs CCI is not clear enough, which may affect your understanding of the task, thereby limiting your enthusiasm for participation					
V21	You are very worried that the submitted solution will be stolen and imitated by SMEs (or others), which affects your willingness to participate					
V22	You are very worried that SMEs will cheat during the program selection process, which affects your willingness to participate					
V23	If the clause of the SMEs CCI does not clearly stipulate the ownership of the intellectual property rights of the solution, your willingness to participate will be seriously affected					
V24	The SMEs CCI is a competitive innovation mode. Once your solution fails to win the bid, all your efforts will be in vain. This will affect your enthusiasm for participation					
V25	Sometimes, you will fail to submit the solution for some special reasons or forget the deadline, which will result in wasted effort. This will affect your enthusiasm for participation					

V26	Participating in the SMEs CCI is generally very beneficial for developing your creativity					
V27	Participating in in the SMEs CCI is generally very beneficial to your work and study					
V28	You think participating in the SMEs CCI will cost you a lot, but it is difficult to get the corresponding return					
V29	There are many uncertain factors in the SMEs CCI, which may cause the final task to be unsolved. This makes you feel a great sense of loss					
V30	You are willing to frequently participate in the SMEs CCI					
V31	You are happy to log into Zbj.com, InnoCentive and other crowdsourcing platforms frequently, and continue to pay attention to CCI projects released by SMEs					
V32	The SMEs CCI platform you chose is very convenient to use					
V33	You can master the rules of crowdsourcing platforms					
V34	Through the crowdsourcing platform, you can easily participate in the SMEs CCI					
V35	You will continue to actively participate in the SMEs CCI in your spare time in the future					
V36	You will continue to find interesting task items on crowdsourcing platforms in the future					

A.2 Screenshots of Data Processing

A.2.1 Screenshots of Frequency Analysis

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	male	105	48.4	48.4	48.4
	female	112	51.6	51.6	100.0
	Total	217	100.0	100.0	

Figure_Apx A- 1 Frequency analysis of gender

Note: "Valid percent" is the percent when missing data are excluded from the calculations.

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	< 20	10	4.6	4.6	4.6
	20-29	143	65.9	65.9	70.5
	30-39	48	22.1	22.1	92.6
	40-49	9	4.1	4.1	96.8
	>50	7	3.2	3.2	100.0
	Total	217	100.0	100.0	

Figure_Apx A- 2 Frequency analysis of age

Highest qualification

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	high school degree or under	6	2.8	2.8	2.8
	higher education degree	32	14.7	14.7	17.5
	bachelor degree	111	51.2	51.2	68.7
	masrer degree	50	23.0	23.0	91.7
	PhD degree	18	8.3	8.3	100.0
	Total	217	100.0	100.0	

Figure_Apx A- 3 Frequency analysis of highest qualification

Monthly income

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	<RMB 3000	46	21.2	21.2	21.2
	RMB 3000-4999	49	22.6	22.6	43.8
	RMB 5000-9999	81	37.3	37.3	81.1
	RMB 10000-19999	35	16.1	16.1	97.2
	>RMB 19999	6	2.8	2.8	100.0
	Total	217	100.0	100.0	

Figure_Apx A- 4 Frequency analysis of monthly income

Number of participations in SMEs CCI

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	never	40	18.4	18.4	18.4
	1-5 times	92	42.4	42.4	60.8
	6-10 times	59	27.2	27.2	88.0
	11-20 times	22	10.1	10.1	98.2
	> 20times	4	1.8	1.8	100.0
	Total	217	100.0	100.0	

Figure_Apx A- 5 Frequency analysis of number of participation in SMEs CCI

Statistics

		v10	v11	v12	v13	v14	v15	v16	v17	v18	v19	v20	v21	v22
N	Valid	217	217	217	217	217	217	217	217	217	217	217	217	217
	Missing	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean		3.76	3.78	3.81	3.83	3.81	3.80	3.86	3.67	3.60	3.31	3.34	3.23	3.25
Std. Error of Mean		.053	.054	.053	.054	.056	.056	.053	.059	.058	.062	.064	.065	.066
Std. Deviation		.788	.802	.785	.796	.820	.818	.775	.876	.856	.909	.940	.962	.970
Variance		.621	.643	.617	.633	.672	.669	.601	.767	.732	.826	.883	.926	.940
Minimum		2	1	2	1	2	1	1	1	1	1	1	1	1
Maximum		5	5	5	5	5	5	5	5	5	5	5	5	5
Percentiles	25	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
	50	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	3.00	3.00	3.00	3.00
	75	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00

Figure_Apx A-6 The mean value and variance of each indicator variable (left half)

v23	v24	v25	v26	v27	v28	v29	v30	v31	v32	v33	v34	v35	v36
217	217	217	217	217	217	217	217	217	217	217	217	217	217
0	0	0	0	0	0	0	0	0	0	0	0	0	0
3.50	3.16	3.13	3.82	3.84	2.92	2.99	3.70	3.56	3.52	3.39	3.47	3.59	3.61
.065	.065	.068	.053	.049	.058	.061	.051	.054	.057	.062	.061	.055	.053
.958	.954	1.003	.776	.718	.860	.900	.757	.798	.834	.906	.892	.807	.781
.918	.911	1.005	.602	.516	.739	.810	.574	.636	.695	.822	.796	.650	.610
1	1	1	2	2	1	1	1	2	1	1	1	1	1
5	5	5	5	5	5	5	5	5	5	5	5	5	5
3.00	2.00	2.00	3.00	3.00	2.00	2.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
4.00	3.00	3.00	4.00	4.00	3.00	3.00	4.00	4.00	4.00	3.00	3.00	4.00	4.00
4.00	4.00	4.00	4.00	4.00	3.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00

Figure_Apx A-7 The mean value and variance of each indicator variable (right half)

A.2.2 Screenshots of Reliability and Validity Analysis

Reliability Statistics

Cronbach's Alpha	N of Items
.593	2

Figure_Apx A- 8 Cronbach's α of MT (material)

Reliability Statistics

Cronbach's Alpha	N of Items
.811	2

Figure_Apx A- 9 Cronbach's α of KAS (knowledge acquisition and sharing)

Reliability Statistics

Cronbach's Alpha	N of Items
.805	3

Figure_Apx A- 10 Cronbach's α of RT (reputation)

Reliability Statistics

Cronbach's Alpha	N of Items
.727	2

Figure_Apx A- 11 Cronbach's α of SB (social belonging)

Reliability Statistics

Cronbach's Alpha	N of Items
.760	2

Figure_Apx A- 12 Cronbach's α of TC (task complexity)

Reliability Statistics

Cronbach's Alpha	N of Items
.871	3

Figure_Apx A- 13 Cronbach's α of IPR (intellectual property right)

Reliability Statistics

Cronbach's Alpha	N of Items
.770	2

Figure_Apx A- 14 Cronbach's α of WOR (waste of resource)

Reliability Statistics

Cronbach's Alpha	N of Items
.836	2

Figure_Apx A- 15 Cronbach's α of BP (benefit perception)

Reliability Statistics

Cronbach's Alpha	N of Items
.703	2

Figure_Apx A- 16 Cronbach's α of CP (cost perception)

Reliability Statistics

Cronbach's Alpha	N of Items
.805	2

Figure_Apx A- 17 Cronbach's α of PW (participation willingness)

Reliability Statistics

Cronbach's Alpha	N of Items
.849	3

Figure_Apx A- 18 Cronbach's α of PU (platform usability)

Reliability Statistics

Cronbach's Alpha	N of Items
.867	2

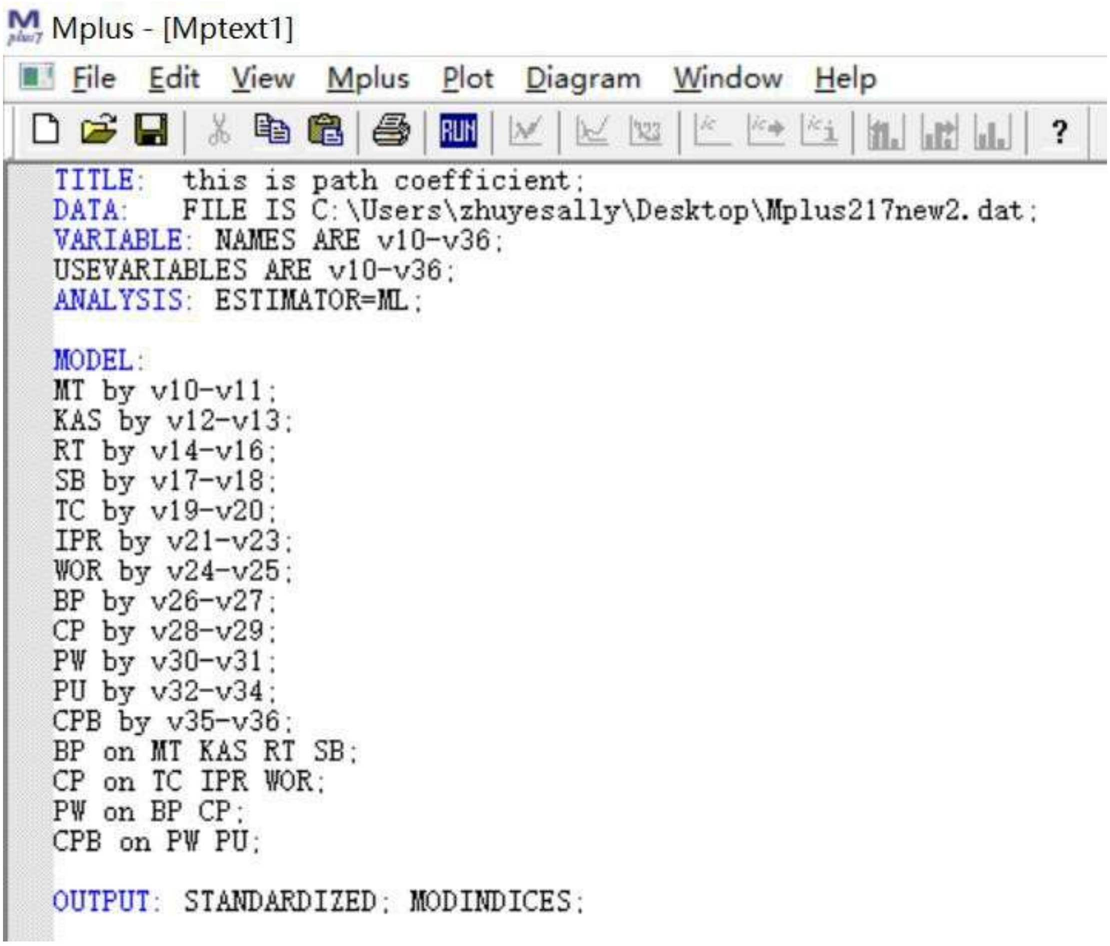
Figure_Apx A- 19 Cronbach's α of CPB (continuous participating behaviour)

Inter-Item Covariance Matrix

	Material	KAS	Reputation	SB	MT	RT	TC	IPR	WOR	BP	CP	PW	PU	CPB
Material	.449	.257	.265	.199	.449	.265	.084	.063	.067	.260	-.036	.166	.207	.185
KAS	.257	.525	.328	.220	.257	.328	.076	.027	.034	.352	-.082	.277	.183	.203
Reputation	.265	.328	.466	.271	.265	.466	.148	.033	.022	.369	-.067	.289	.234	.230
SB	.199	.220	.271	.589	.199	.271	.119	.129	.048	.269	.025	.231	.221	.216
MT	.449	.257	.265	.199	.449	.265	.084	.063	.067	.260	-.036	.166	.207	.185
RT	.265	.328	.466	.271	.265	.466	.148	.033	.022	.369	-.067	.289	.234	.230
TC	.084	.076	.148	.119	.084	.148	.689	.219	.274	.089	.240	.030	.074	.103
IPR	.063	.027	.033	.129	.063	.033	.219	.737	.419	.020	.399	-.028	.034	.018
WOR	.067	.034	.022	.048	.067	.022	.274	.419	.779	.005	.434	-.023	.035	.011
BP	.260	.352	.369	.269	.260	.369	.089	.020	.005	.480	-.077	.321	.224	.217
CP	-.036	-.082	-.067	.025	-.036	-.067	.240	.399	.434	-.077	.597	-.134	-.095	-.091
PW	.166	.277	.289	.231	.166	.289	.030	-.028	-.023	.321	-.134	.506	.282	.282
PU	.207	.183	.234	.221	.207	.234	.074	.034	.035	.224	-.095	.282	.592	.397
CPB	.185	.203	.230	.216	.185	.230	.103	.018	.011	.217	-.091	.282	.397	.556

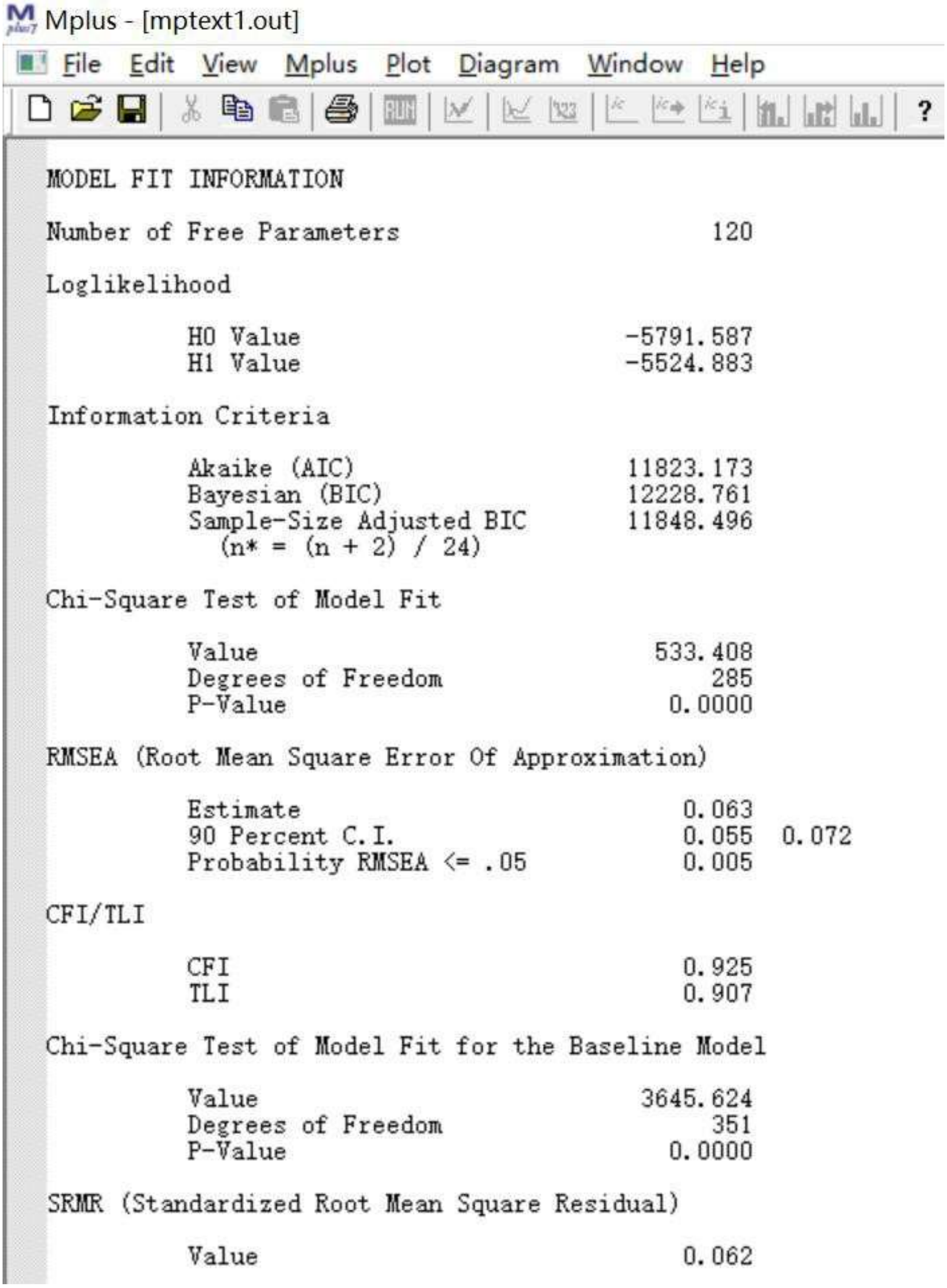
Figure_Apx A- 20 Covariance matrix of latent variables

A.2.3 Screenshots of Data Processing in Mplus7



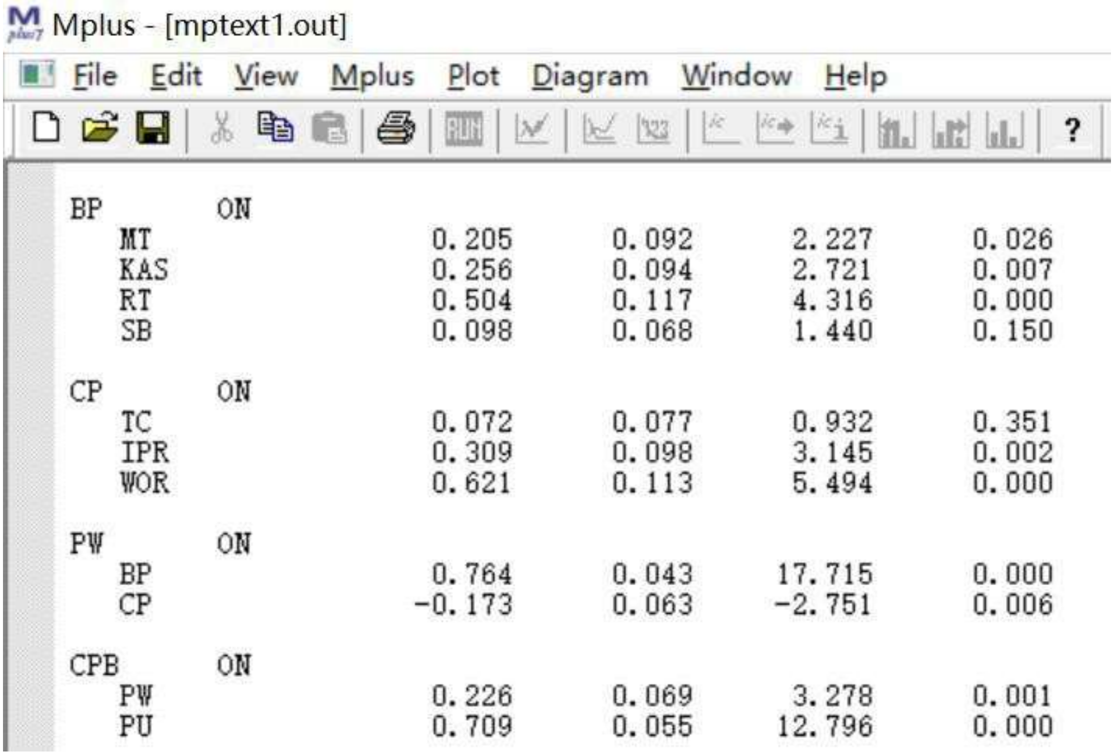

```
TITLE:  this is path coefficient;
DATA:   FILE IS C:\Users\zhuyesally\Desktop\Mplus217new2.dat;
VARIABLE: NAMES ARE v10-v36;
USEVARIABLES ARE v10-v36;
ANALYSIS: ESTIMATOR=ML;

MODEL:
MT by v10-v11;
KAS by v12-v13;
RT by v14-v16;
SB by v17-v18;
TC by v19-v20;
IPR by v21-v23;
WOR by v24-v25;
BP by v26-v27;
CP by v28-v29;
PW by v30-v31;
PU by v32-v34;
CPB by v35-v36;
BP on MT KAS RT SB;
CP on TC IPR WOR;
PW on BP CP;
CPB on PW PU;

OUTPUT: STANDARDIZED; MODINDICES;
```

Figure_Apx A- 21 Program of model fit and path coefficient analysis



```
Mplus - [mptext1.out]
File  Edit  View  Mplus  Plot  Diagram  Window  Help

MODEL FIT INFORMATION

Number of Free Parameters                        120

Loglikelihood

          H0 Value                         -5791.587
          H1 Value                         -5524.883

Information Criteria

          Akaike (AIC)                     11823.173
          Bayesian (BIC)                   12228.761
          Sample-Size Adjusted BIC         11848.496
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit

          Value                              533.408
          Degrees of Freedom                     285
          P-Value                             0.0000

RMSEA (Root Mean Square Error Of Approximation)

          Estimate                             0.063
          90 Percent C.I.                      0.055  0.072
          Probability RMSEA <= .05             0.005

CFI/TLI

          CFI                                  0.925
          TLI                                  0.907

Chi-Square Test of Model Fit for the Baseline Model

          Value                             3645.624
          Degrees of Freedom                     351
          P-Value                             0.0000

SRMR (Standardized Root Mean Square Residual)

          Value                                0.062
```

Figure_Apx A- 22 Model fit information

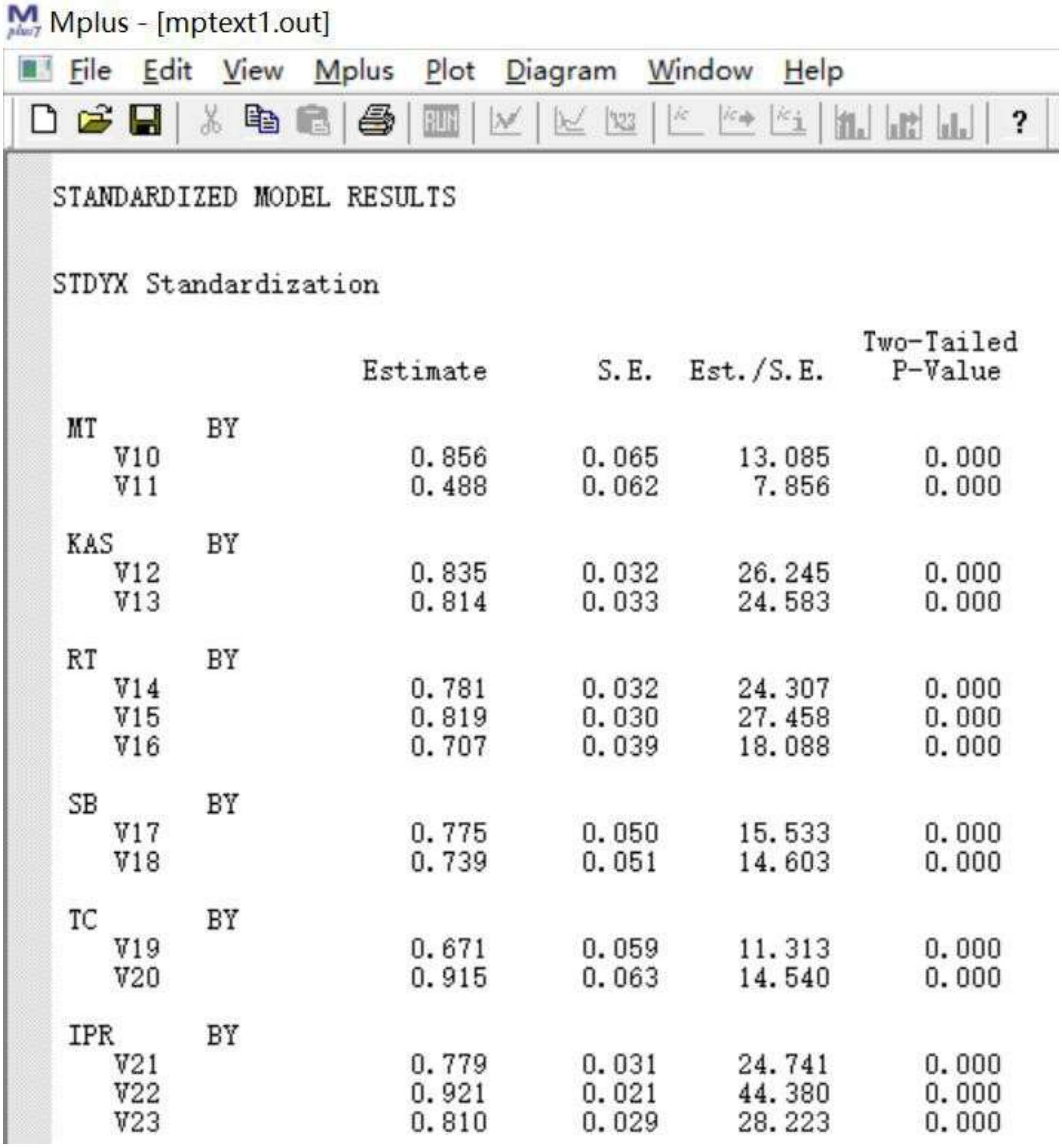


Mplus - [mptext1.out]

File Edit View Mplus Plot Diagram Window Help

BP	ON				
	MT	0.205	0.092	2.227	0.026
	KAS	0.256	0.094	2.721	0.007
	RT	0.504	0.117	4.316	0.000
	SB	0.098	0.068	1.440	0.150
CP	ON				
	TC	0.072	0.077	0.932	0.351
	IPR	0.309	0.098	3.145	0.002
	WOR	0.621	0.113	5.494	0.000
PW	ON				
	BP	0.764	0.043	17.715	0.000
	CP	-0.173	0.063	-2.751	0.006
CPB	ON				
	PW	0.226	0.069	3.278	0.001
	PU	0.709	0.055	12.796	0.000

Figure_Apx A- 23 Parameter estimation and hypothesis testing


Mplus - [mptext1.out]

File Edit View Mplus Plot Diagram Window Help

STANDARDIZED MODEL RESULTS

STDYX Standardization

		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
MT	BY				
V10		0.856	0.065	13.085	0.000
V11		0.488	0.062	7.856	0.000
KAS	BY				
V12		0.835	0.032	26.245	0.000
V13		0.814	0.033	24.583	0.000
RT	BY				
V14		0.781	0.032	24.307	0.000
V15		0.819	0.030	27.458	0.000
V16		0.707	0.039	18.088	0.000
SB	BY				
V17		0.775	0.050	15.533	0.000
V18		0.739	0.051	14.603	0.000
TC	BY				
V19		0.671	0.059	11.313	0.000
V20		0.915	0.063	14.540	0.000
IPR	BY				
V21		0.779	0.031	24.741	0.000
V22		0.921	0.021	44.380	0.000
V23		0.810	0.029	28.223	0.000

Figure_Apx A- 24 Path coefficient of indicator variables (Part 1)

WOR	BY				
V24		0.852	0.038	22.669	0.000
V25		0.727	0.041	17.590	0.000
BP	BY				
V26		0.887	0.021	42.058	0.000
V27		0.815	0.028	29.598	0.000
CP	BY				
V28		0.724	0.043	16.955	0.000
V29		0.762	0.041	18.615	0.000
PW	BY				
V30		0.855	0.034	25.010	0.000
V31		0.788	0.037	21.181	0.000
PU	BY				
V32		0.791	0.033	24.216	0.000
V33		0.846	0.028	30.200	0.000
V34		0.785	0.033	23.946	0.000
CPB	BY				
V35		0.899	0.026	35.121	0.000
V36		0.844	0.028	29.892	0.000

Figure_Apx A- 25 Path coefficient of indicator variables (Part 2)

A.3 Calculation Methods of the Value of CR and AVE of Each Latent Variable in Microsoft Excel

(Taking latent variable – MT as an example)

Step 1: Getting the factor loading (normalised) in SPSS, action: Analyse → Data Reduction → Factor → Factor Analysis

Step 2: As latent variable MT has two indicator items: v10 and v11, naming A1 = the factor loading (normalised) of v10, A2 = the factor loading (normalised) of v11.

Step 3: Calculating the squared multiple correlation (SMC) of v10 and v11. Naming B1 = SMC of v10 = IF(POWER(A1,2)=0,"",POWER(A1,2)), B2= SMC of v11 = IF(POWER(A2,2)=0,"",POWER(A1,2)). *Note:* 2 represents the number of the indicator items of each latent variable.

Step 4: CR = SUM(A1:A2)*SUM(A1*A2)/(SUM(A1:A2)*SUM(A1:A2)+SUM((1-B1):(1-B2)))

AVE = AVERAGE((1-B1):(1-B2))

Appendix B The Screenshots of Numerical Simulation in MATLAB 7.0, Model Solving Process and Result Proof of Chapters 3-5

B.1 The Screenshots of Numerical Simulation in MATLAB 7.0 of Chapters 3-5

B.1.1 The Screenshots of Numerical Simulation in MATLAB 7.0 of Chapter 3

File Edit Text Desktop Window Help

```
clc
syms x b N q k B r ramda cml
k=1
x=1.2
S=0.1

N=3
cmT1=N^2*x^2*((1+b)^3*N^2+(1+b)*(b^2-2)*N+ 1-b)/(2*k*((1+b)^2*N-1)^2)-N*S
cmN1=N*x^2/(2*k*(1+b))-N*S

 z2=ezplot(simplify(cmT1),[0,2])
  set(z2,'LineStyle','-','LineWidth',2,'Color','r')
hold on
 z2=ezplot(simplify(cmN1),[0,2])
  set(z2,'LineStyle','--','LineWidth',2,'Color','r')
hold on

 N=5
cmT1=N^2*x^2*((1+b)^3*N^2+(1+b)*(b^2-2)*N+ 1-b)/(2*k*((1+b)^2*N-1)^2)-N*S
cmN1=N*x^2/(2*k*(1+b))-N*S

 z2=ezplot(simplify(cmT1),[0,2])
  set(z2,'LineStyle','-','LineWidth',2,'Color','g')
hold on
 z2=ezplot(simplify(cmN1),[0,2])
  set(z2,'LineStyle','--','LineWidth',2,'Color','g')
hold on
```

Figure_Apx B-1 Seeker's deterministic income when the retained task volume is low (Part 1)

```

N=8
cmT1=N^2*x^2*((1+b)^3*N^2+(1+b)*(b^2-2)*N+ 1-b)/(2*k*((1+b)^2*N-1)^2)-N*S
cmN1=N*x^2/(2*k*(1+b))-N*S

 z2=ezplot(simplify(cmT1),[0,2])
  set(z2,'LineStyle','-','LineWidth',2,'Color','b')
hold on
 z2=ezplot(simplify(cmN1),[0,2])
  set(z2,'LineStyle','--','LineWidth',2,'Color','b')
hold on


axis([0 2 0 30])



legend('TR','NR')
xlabel('b')
ylabel('CM')
```

Figure_Apx B- 2 Seeker's deterministic income when the retained task volume is low (Part 2)

File Edit Text Desktop Window Help

```
clc
syms x b N q k B r ramda cm1
k=0.8
x=1.2
S=0.15



N=5
q=24
Q=N^2*x^2*(N-1+(N+1)*b)/(((1+b)^2*N-1)*k)
B=(((1+b)*N-1)*q*k-N^2*(N-1)*x^2)/(N*x*(2*b*N+N-1))
e=(((1+b)*N+b-1)*q*k-N*(N-1)^2*x^2)/(N*x*(2*b*N+N-1))
r=(b*q*k+N*(N-1)*x^2)/(N*x^2*(2*b*N+N-1))
cm= simplify(q- N*((B+x*r)^2+(N-1)*x^2*r^2+b*(B^2+N*x^2*r^2))/(2*k)-N*S)
 z2=ezplot(simplify(cm),[0,2])
  set(z2,'LineStyle','-','LineWidth',2,'Color','r')
hold on

q=27
Q=N^2*x^2*(N-1+(N+1)*b)/(((1+b)^2*N-1)*k)
B=(((1+b)*N-1)*q*k-N^2*(N-1)*x^2)/(N*x*(2*b*N+N-1))
e=(((1+b)*N+b-1)*q*k-N*(N-1)^2*x^2)/(N*x*(2*b*N+N-1))
r=(b*q*k+N*(N-1)*x^2)/(N*x^2*(2*b*N+N-1))
cm= simplify(q- N*((B+x*r)^2+(N-1)*x^2*r^2+b*(B^2+N*x^2*r^2))/(2*k)-N*S)
 z2=ezplot(simplify(cm),[0,2])
  set(z2,'LineStyle','-','LineWidth',2,'Color','g')
hold on
```

Figure_Apx B-3 Seeker's deterministic economic benefit under TR mode when the retained task volume is high (Part 1)

```
q=30
Q=N^2*x^2*(N-1+(N+1)*b)/(((1+b)^2*N-1)*k)
B=(((1+b)*N-1)*q*k-N^2*(N-1)*x^2)/(N*x*(2*b*N+N-1))
e=(((1+b)*N+b-1)*q*k-N*(N-1)^2*x^2)/(N*x*(2*b*N+N-1))
r=(b*q*k+N*(N-1)*x^2)/(N*x^2*(2*b*N+N-1))
cm= simplify(q- N*((B+x*r)^2+(N-1)*x^2*r^2+b*(B^2+N*x^2*r^2))/(2*k)-N*S)
 z2=ezplot(simplify(cm),[0,2])
  set(z2,'LineStyle','-','LineWidth',2,'Color','b')
hold on


xlabel('b')
ylabel('CM')

axis([0.2 1.6 -2 16])
```

Figure_Apx B-4 Seeker's deterministic economic benefit under TR mode when the retained task volume is high (Part 2)

B.1.2 The Screenshots of Numerical Simulation in MATLAB 7.0 of Chapter 4

File Edit Text Desktop Window Help

```
clc
syms k u  deltae deltar delta1 delta2 ru a e0 e1 e2 beta0 beta1 beta2 v
syms phi enta n

k=100
u=80
ru=1
a=0
deltae=25
deltar= enta*deltae/((1-enta)*ru^2)

delta1=sqrt((ru^2*deltar+deltae)*2*3.14)
delta2=sqrt((ru^2*enta*deltar+deltae)*2*3.14)

n=5
m1=2
e0= k/(u*n)
e1=k*phi*(1-enta)/(u*n)
v=ru*a+enta*(m1-k*e1-ru*a)
beta2=n*delta2*u/(n*delta2*u+(n-1)*(k^2*phi + n*u*v))
beta0=n*delta1*u/(n*delta1*u+(n-1)*k^2)
beta1=n*delta1*u*(enta*beta2+(1-enta))/(n*delta1*u+(n-1)*((1-enta)*k^2*phi+n*u*ru*a))

z1=ezplot(e0-e1,[0 1 1 2])
  set(z1,'LineStyle','-','LineWidth',2,'Color','r')
hold on

axis([0 0.95 1 2])
xlabel('\Gamma')
ylabel('\phi')
```

Figure_Apx B- 5 The effect of $<p, T$ on the relationship between e^*_1 and e^*_0

```
clc
syms k u  deltae deltar delta1 delta2 ru a e0 e1 e2 beta0 beta1 beta2 v
syms phi enta n

k=100
u=80
ru=1
a=0
deltae=25

phi=1.2
enta=0.3
deltar= enta*deltae/((1-enta)*ru^2)
delta1=sqrt((ru^2*deltar+deltae)*2*3.14)
delta2=sqrt((ru^2*enta*deltar+deltae)*2*3.14)
m1=2
e0= k/(u*n)
e1=k*phi*(1-enta)/(u*n)
v=ru*a+enta*(m1-k*e1-ru*a)
beta2=n*delta2*u/(n*delta2*u+(n-1)*(k^2*phi + n*u*v))
beta0=n*delta1*u/(n*delta1*u+(n-1)*k^2)
beta1=n*delta1*u*(enta*beta2+(1-enta))/(n*delta1*u+(n-1)*((1-enta)*k^2*phi+n*u*ru*a))

z1=ezplot(simplify(e0)-simplify(e1),[2 20])
  set(z1,'LineStyle','--','LineWidth',2,'Color','b')
hold on

```

Figure_Apx B- 6 The effect of n on $e_1^* - e_0^*$ (Part 1)

```
phi=1.5
enta=0.3
deltar= enta*deltae/((1-enta)*ru^2)
delta1=sqrt((ru^2*deltar+deltae)*2*3.14)
delta2=sqrt((ru^2*enta*deltar+deltae)*2*3.14)
m1=2
e0= k/(u*n)
e1=k*phi*(1-enta)/(u*n)
v=ru*a+enta*(m1-k*e1-ru*a)
beta2=n*delta2*u/(n*delta2*u+(n-1)*(k^2*phi + n*u*v))
beta0=n*delta1*u/(n*delta1*u+(n-1)*k^2)
beta1=n*delta1*u*(enta*beta2+(1-enta))/(n*delta1*u+(n-1)*((1-enta)*k^2*phi+n*u*ru*a))

z1=ezplot(simplify(e0)-simplify(e1),[2 20])
  set(z1,'LineStyle','-','LineWidth',2,'Color','b')
hold on

legend('\phi=1.2,\Gamma=0.3','\phi=1.5,\Gamma=0.3')
xlabel('n')
ylabel('e_0^*-e_1^*')
axis([2 20 -0.1 0.15])
```

Figure_Apx B-7 The effect of n on $e_1^* - e_0^*$ (Part 2)

```
clc
syms k u  deltae deltar delta1 delta2 ru a e0 e1 e2 beta0 beta1 beta2 v
syms phi enta n

k=100
u=50
ru=1
a=0
deltae=100
deltar= enta*deltae/((1-enta)*ru^2)

delta1=sqrt((ru^2*deltar+deltae)*2*3.14)
delta2=sqrt((ru^2*enta*deltar+deltae)*2*3.14)

n=3
m1=2
e0= k/(u*n)
e1=k*phi*(1-enta)/(u*n)
v=ru*a+enta*(m1-k*e1-ru*a)
beta2=n*delta2*u/(n*delta2*u+(n-1)*(k^2*phi + n*u*v))
beta0=n*delta1*u/(n*delta1*u+(n-1)*k^2)
beta1=n*delta1*u*(enta*beta2+(1-enta))/(n*delta1*u+(n-1)*((1-enta)*k^2*phi+n*u*ru*a))

z1=ezplot(simplify(beta0)-simplify(beta1),[0 0.95 1 2])
  set(z1,'LineStyle','-','LineWidth',2,'Color','r')
hold on
```

Figure_Apx B- 8 The effect of $<p, T$ on the relationship between P^*_1 and P^*_0 (Part 1)

```

n=6
m1=2
e0= k/(u*n)
e1=k*phi*(1-enta)/(u*n)
v=ru*a+enta*(m1-k*e1-ru*a)
beta2=n*delta2*u/(n*delta2*u+(n-1)*(k^2*phi + n*u*v))
beta0=n*delta1*u/(n*delta1*u+(n-1)*k^2)
beta1=n*delta1*u*(enta*beta2+(1-enta))/(n*delta1*u+(n-1)*((1-enta)*k^2*phi+n*u*ru*a))
 z1=ezplot(simplify(beta0)-simplify(beta1),[0 0.95 1 2])
  set(z1,'LineStyle','--','LineWidth',2,'Color','g')
hold on

n=10
m1=2
e0= k/(u*n)
e1=k*phi*(1-enta)/(u*n)
v=ru*a+enta*(m1-k*e1-ru*a)
beta2=n*delta2*u/(n*delta2*u+(n-1)*(k^2*phi + n*u*v))
beta0=n*delta1*u/(n*delta1*u+(n-1)*k^2)
beta1=n*delta1*u*(enta*beta2+(1-enta))/(n*delta1*u+(n-1)*((1-enta)*k^2*phi+n*u*ru*a))
 z1=ezplot(simplify(beta0)-simplify(beta1),[0 0.95 1 2])
  set(z1,'LineStyle','-.','LineWidth',2,'Color','b')
```

Figure_Apx B-9 The effect of $<p, T$ on the relationship between P^*_1 and P^*_0 (Part 2)

```
hold on

n=30
m1=2
e0= k/(u*n)
e1=k*phi*(1-enta)/(u*n)
v=ru*a+enta*(m1-k*e1-ru*a)
beta2=n*delta2*u/(n*delta2*u+(n-1)*(k^2*phi + n*u*v))
beta0=n*delta1*u/(n*delta1*u+(n-1)*k^2)
beta1=n*delta1*u*(enta*beta2+(1-enta))/(n*delta1*u+(n-1)*((1-enta)*k^2*phi+n*u*ru*a))

z1=ezplot(simplify(beta0)-simplify(beta1),[0 0.95 1 2])
  set(z1,'LineStyle','-','LineWidth',2,'Color','r')
hold on

axis([0 0.95 1 1.05])
xlabel('\Gamma')
ylabel('\phi')
```

Figure_Apx B-10 The effect of $<p, T$ on the relationship between P^*_1 and P^*_0 (Part 3)

```
clc
syms k u  deltae deltar delta1 delta2 ru a e0 e1 e2 beta0 beta1 beta2 v
syms phi enta n

k=100
u=50
ru=1
a=0
deltae=100

phi=1.02
enta=0.5
deltar= enta*deltae/((1-enta)*ru^2)
delta1=sqrt((ru^2*deltar+deltae)*2*3.14)
delta2=sqrt((ru^2*enta*deltar+deltae)*2*3.14)
m1=2
e0= k/(u*n)
e1=k*phi*(1-enta)/(u*n)
v=ru*a+enta*(m1-k*e1-ru*a)
beta2=n*delta2*u/(n*delta2*u+(n-1)*(k^2*phi + n*u*v))
beta0=n*delta1*u/(n*delta1*u+(n-1)*k^2)
beta1=n*delta1*u*(enta*beta2+(1-enta))/(n*delta1*u+(n-1)*((1-enta)*k^2*phi+n*u*ru*a))

z1=ezplot(simplify(beta0)-simplify(beta1),[2 20])
  set(z1,'LineStyle','-','LineWidth',2,'Color','r')
hold on

```

Figure_Apx B- 11 The effect of n on $P^*_1 - P^*_0$ (Part 1)

```
phi=1.02
enta=0.6
deltar= enta*deltae/((1-enta)*ru^2)
delta1=sqrt((ru^2*deltar+deltae)*2*3.14)
delta2=sqrt((ru^2*enta*deltar+deltae)*2*3.14)
m1=2
e0= k/(u*n)
e1=k*phi*(1-enta)/(u*n)
v=ru*a+enta*(m1-k*e1-ru*a)
beta2=n*delta2*u/(n*delta2*u+(n-1)*(k^2*phi + n*u*v))
beta0=n*delta1*u/(n*delta1*u+(n-1)*k^2)
beta1=n*delta1*u*(enta*beta2+(1-enta))/(n*delta1*u+(n-1)*((1-enta)*k^2*phi+n*u*ru*a))

z1=ezplot(simplify(beta0)-simplify(beta1),[2 20])
  set(z1,'LineStyle','—','LineWidth',2,'Color','g')
hold on

phi=1.03
enta=0.5
deltar= enta*deltae/((1-enta)*ru^2)
delta1=sqrt((ru^2*deltar+deltae)*2*3.14)
delta2=sqrt((ru^2*enta*deltar+deltae)*2*3.14)
m1=2
e0= k/(u*n)
e1=k*phi*(1-enta)/(u*n)
v=ru*a+enta*(m1-k*e1-ru*a)
beta2=n*delta2*u/(n*delta2*u+(n-1)*(k^2*phi + n*u*v))
beta0=n*delta1*u/(n*delta1*u+(n-1)*k^2)
beta1=n*delta1*u*(enta*beta2+(1-enta))/(n*delta1*u+(n-1)*((1-enta)*k^2*phi+n*u*ru*a))

```

Figure_Apx B- 12 The effect of n on $P_1^* - P_0^*$ (Part 2)

```
z1=ezplot(simplify(beta0)-simplify(beta1),[2 20])
  set(z1,'LineStyle','-.','LineWidth',2,'Color','b')
hold on

legend('\phi=1.02,\Gamma=0.5','\phi=1.02,\Gamma=0.6','\phi=1.03,\Gamma=0.5')
xlabel('n')
ylabel('\beta_0^*-\beta_1^*')

axis([2 20 -3*10^(-3) 3.5*10^(-3)])

```

Figure_Apx B- 13 The effect of n on $P_1^* - P_0^*$ (Part 3)

B.1.3 The Screenshots of Numerical Simulation in MATLAB 7.0 of Chapter 5

```
clc
syms enta A k beta ce h u randa n
syms ei zi h pin
ce=0.4
h=0.2
A=5
u=2
n=8

enta=0.8
beta=0.2
k=0.1
zita=0.4
ei=A*(n-1)*enta*(n*randa+1)/(u*ce*n^2*((n-1)*randa+1))
zi=(((n-1)*randa+1)*beta + k*ce)/(2*((n-1)*randa+1)*n*h)
h=(((n-1)*randa+1)*beta - k*ce)/(2*((n-1)*randa+1)*n*zita)

pin=A/n + h*zita*zi - ce*(ei-k*zi)-h*zi^2/2
pin1=(((n-1)*randa+1)*beta+k*ce)*(((n-1)*randa+1)*beta+(4*n*(n-1)*randa+4*n-3)*k*ce)/(8*n^2*h*((n-1)*randa+1)^2) + A*(1-(n*randa+1)*(n-1)*enta/(((n-1)*randa+1)*u*n))/n
z1=ezplot(pin1,[0,1])
  set(z1,'LineStyle','-','LineWidth',2,'Color','b')
hold on

enta=0.5
beta=0.2
k=0.1
pin1=(((n-1)*randa+1)*beta+k*ce)*(((n-1)*randa+1)*beta+(4*n*(n-1)*randa+4*n-3)*k*ce)/(8*n^2*h*((n-1)*randa+1)^2) + A*(1-(n*randa+1)*(n-1)*enta/(((n-1)*randa+1)*u*n))/n
z1=ezplot(pin1,[0,1])
  set(z1,'LineStyle','--','LineWidth',2,'Color','g')
hold on
```

Figure_Apx B-14 The impact of fairness concern sensitivity on solvers' expected return (Part 1)

```


enta=0.2
beta=0.2
k=0.1
pin1=(((n-1)*randa+1)*beta+k*ce)*(((n-1)*randa+1)*beta+(4*n*(n-1)*randa+4*n-3)*k*ce)/(8*n^2*h*((n-1)*randa+1)^2) + A*(1-(n*randa+1)*(n-1)*enta/(((n-1)*randa+1)*u*n))/n
z1=ezplot(pin1,[0,1])
  set(z1,'LineStyle','-.','LineWidth',2,'Color','r')
hold on


axis([0 1 0.37 0.63])
```

Figure_Apx B-15 The impact of fairness concern sensitivity on solvers' expected return (Part 2)

```
clc
syms enta A k beta cs h u randa n
syms ei zi b pin
cs=0.4
h=0.2
A=20
u=2

enta=1
beta=0.6
k=0.3
zita=0.4

randa=0.1
pin1=(((n-1)*randa+1)*beta*k*cs)*(((n-1)*randa+1)*beta+(4*n*(n-1)*randa+4*n-3)*k*cs)/(8*n^2*h*((n-1)*randa+1)^2) + A*(1-(n*randa+1)*(n-1)*enta/(((n-1)*randa+1)*u*n))/n
z1=ezplot(pin1,[5,30])
  set(z1,'LineStyle','-','LineWidth',2,'Color','r')
hold on

```

Figure_Apx B-16 The impact of the number of solvers on solvers' expected return (Part 1)

```
randa=0.5
pin1=(((n-1)*randa+1)*beta*k*cs)*(((n-1)*randa+1)*beta+(4*n*(n-1)*randa+4*n-3)*k*cs)/(8*n^2*h*((n-1)*randa+1)^2) + A*(1-(n*randa+1)*(n-1)*enta/(((n-1)*randa+1)*u*n))/n
z1=ezplot(pin1,[5,30])
  set(z1,'LineStyle','--','LineWidth',2,'Color','g')
hold on

randa=0.9
pin1=(((n-1)*randa+1)*beta*k*cs)*(((n-1)*randa+1)*beta+(4*n*(n-1)*randa+4*n-3)*k*cs)/(8*n^2*h*((n-1)*randa+1)^2) + A*(1-(n*randa+1)*(n-1)*enta/(((n-1)*randa+1)*u*n))/n
z1=ezplot(pin1,[5,30])
  set(z1,'LineStyle','-.','LineWidth',2,'Color','b')
hold on

axis([5 15 8.7 1.8])
legend('\lambda=0.1','\lambda=0.5','\lambda=0.9')
```

Figure_Apx B-17 The impact of the number of solvers on solvers' expected return (Part 2)

```
clc
syms enta A k beta cs h u randa n
syms ei zi b pin

cs=0.4
h=0.2
u=2

enta=0.2
beta=0.6
k=0.2
zita=0.4
A=5
n=5
enks=enta^2*(randa+1)*(n-1)
zeks=((randa+1)*k*cs-beta*randa)/((randa+1)*n*h)
Aeks=(enta*(randa+1)^2*u*n^2*(n-1)*cs+randa*u*n^2)/((randa+1)*(n-1))
piisks=Aeks/n -cs*(enks-k*zeks)-h*zeks^2/2
piinkrs=((k*cs*(randa+1)*(2*n-1)+randa*beta)*(k*cs*(randa+1)-randa*beta))/(2*n^2*h*(randa+1)^2)+ u*n*(enta*(randa+1)^2*(n-1)*cs+randa)/((randa+1)*(n-1))-enta^2*cs*(randa+1)*(n
eks=enta^2*(randa+1)*(n-1)
Aks=(enta*(randa+1)^2*u*n^2*(n-1)*cs+randa*u*n^2)/((randa+1)*(n-1))
zks=((randa+1)*k*cs+(n*randa+1)*beta)/(2*(randa+1)*n*h)
b=(((n+2)*randa+1)*beta-(randa+1)*k*cs)/(2*((n+1)*randa+1)*n*zita)
zksy=((randa+1)*k*cs-beta*randa+((n+1)*randa+1)*n*zita*b)/((randa+1)*n*h)
piiks=Aks/n + b*zita*zks-cs*(eks-k*zks)-h*zks^2/2

z1=ezplot(piiks-piinks,[0,1])
  set(z1,'LineStyle','-','LineWidth',2,'Color','r')
hold on
```

Figure_Apx B-18 The impact of fairness concern sensitivity and the number of solvers on the economic value of knowledge sharing incentives (Part 1)

```
n=10
enkz=enta^2*(randa+1)*(n-1)
znkz=((randa+1)*k*ce-beta*randa)/((randa+1)*n*h)
Ankz=(enta*(randa+1)^2*u*n^2*(n-1)*ce+randa*u*n^2)/((randa+1)*(n-1))
piinkz=Ankz/n -ce*(enkz-k*znkz)-h*znkz^2/2
piinkzz=((k*ce*(randa+1)*(2*n-1)+randa*beta)*(k*ce*(randa+1)-randa*beta))/(2*n^2*h*(randa+1)^2)+ u*n*(enta*(randa+1)^2*(n-1)*ce+randa)/((randa+1)*(n-1)) - enta^2*ce*(randa+1)*
pifnkz=enta*log(enkz)+beta*znkz - Ankz
ekz=enta^2*(randa+1)*(n-1)
Akz=(enta*(randa+1)^2*u*n^2*(n-1)*ce+randa*u*n^2)/((randa+1)*(n-1))
zkz=((randa+1)*k*ce+(n*randa+1)*beta)/(2*(randa+1)*n*h)
b=(((n+2)*randa+1)*beta-(randa+1)*k*ce)/(2*((n+1)*randa+1)*n*zita)
zkzy=((randa+1)*k*ce-beta*randa+((n+1)*randa+1)*n*zita*b)/((randa+1)*n*h)
piikz=Akz/n + b*zita*zkz-ce*(ekz-k*zkz)-h*zkz^2/2
pifkz=enta*log(ekz)+beta*zkz - Akz-n*b*zita*zkz


z1=ezplot(piikz-piinkz,[0,1])
  set(z1,'LineStyle','--','LineWidth',2,'Color','g')
hold on
```

Figure_Apx B-19 The impact of fairness concern sensitivity and the number of solvers on the economic value of knowledge sharing incentives (Part 2)

```
n=15
enkz=enta^2*(randa+1)*(n-1)
znkz=((randa+1)*k*ce-beta*randa)/((randa+1)*n*h)
Ankz=(enta*(randa+1)^2*u*n^2*(n-1)*ce+randa*u*n^2)/((randa+1)*(n-1))
piinkz=Ankz/n -ce*(enkz-k*znkz)-h*znkz^2/2
piinkzz=((k*ce*(randa+1)*(2*n-1)+randa*beta)*(k*ce*(randa+1)-randa*beta))/(2*n^2*h*(randa+1)^2)+ u*n*(enta*(randa+1)^2*(n-1)*ce+randa)/((randa+1)*(n-1)) - enta^2*ce*(randa+1)*
pifnkz=enta*log(enkz)+beta*znkz - Ankz
ekz=enta^2*(randa+1)*(n-1)
Akz=(enta*(randa+1)^2*u*n^2*(n-1)*ce+randa*u*n^2)/((randa+1)*(n-1))
zkz=((randa+1)*k*ce+(n*randa+1)*beta)/(2*(randa+1)*n*h)
b=(((n+2)*randa+1)*beta-(randa+1)*k*ce)/(2*((n+1)*randa+1)*n*zita)
zkzy=((randa+1)*k*ce-beta*randa+((n+1)*randa+1)*n*zita*b)/((randa+1)*n*h)
piikz=Akz/n + b*zita*zkz-ce*(ekz-k*zkz)-h*zkz^2/2
pifkz=enta*log(ekz)+beta*zkz - Akz-n*b*zita*zkz
z1=ezplot(piikz-piinkz,[0,1])
  set(z1,'LineStyle','--','LineWidth',2,'Color','b')
hold on
```

Figure_Apx B-20 The impact of fairness concern sensitivity and the number of solvers on the economic value of knowledge sharing incentives (Part 3)

```
n=25
enkz=enta^2*(randa+1)*(n-1)
znkz=((randa+1)*k*ce-beta*randa)/((randa+1)*n*h)
Ankz=(enta*(randa+1)^2*u*n^2*(n-1)*ce+randa*u*n^2)/((randa+1)*(n-1))
piinkz=Ankz/n -ce*(enkz-k*znkz)-h*znkz^2/2
piinkzz=((k*ce*(randa+1)*(2*n-1)+randa*beta)*(k*ce*(randa+1)-randa*beta))/(2*n^2*h*(randa+1)^2)+ u*n*(enta*(randa+1)^2*(n-1)*ce+randa)/((randa+1)*(n-1)) - enta^2*ce*(randa+1)*
pifnkz=enta*log(enkz)+beta*znkz - Ankz
ekz=enta^2*(randa+1)*(n-1)
Akz=(enta*(randa+1)^2*u*n^2*(n-1)*ce+randa*u*n^2)/((randa+1)*(n-1))
zkz=((randa+1)*k*ce+(n*randa+1)*beta)/(2*(randa+1)*n*h)
b=(((n+2)*randa+1)*beta-(randa+1)*k*ce)/(2*((n+1)*randa+1)*n*zita)
zkzy=((randa+1)*k*ce-beta*randa+((n+1)*randa+1)*n*zita*b)/((randa+1)*n*h)
piikz=Akz/n + b*zita*zkz-ce*(ekz-k*zkz)-h*zkz^2/2
pifkz=enta*log(ekz)+beta*zkz - Akz-n*b*zita*zkz

z1=ezplot(piikz-piinkz,[0,1])
  set(z1,'LineStyle','-','LineWidth',2,'Color','c')
hold on


axis([0 1 0 0.06])
xlabel('\lambda')
ylabel('\pi^{KS*}-\pi^{NKS*}')
```

Figure_Apx B-21 The impact of fairness concern sensitivity and the number of solvers on the economic value of knowledge sharing incentives (Part 4)

B.2 Model Solving Process and Result Proof of Chapters 3-5

B.2.1 Model Solving Process and Result Proof of Chapter 3

1. Equilibrium solution of TR model (similar to the solving process of NR model)

First, solving the incentive constraint IC in Equation (3- 7). Obviously, the Hessian matrix (Chen, Pingge, 2017) $_{Ic} = \begin{vmatrix} -k & 0 \\ 0 & -k \end{vmatrix}$ is negative definite. Thus, from the first-order derivative of cE_i with respective to e_i and E_{ij}, which are $\frac{acE_i}{ae_i} = 0, \frac{acEi}{aE_{ij}} = 0$, then it is got:

$$e_i = \frac{\{3 + yx_0}{k}, E_{ij} = \frac{yx_0}{k} \qquad \textbf{(Apx\_B2-1)}$$

It can be seen that the self-interest effort e_i of the solver is related to both the personal performance incentive coefficient $\{3$ and the total performance incentive coefficient y, while the altruistic effort E_{ij} is only related to the total performance output incentive coefficient y.

Second, solving the IR constraint. The rational seeker will not allow any solver to get a higher return than the retained utility, so take the equal sign of IR and substitute it into Equation (3- 6). and substitute and simplify the expressions of e_i and E_{ij} into Equation (3- 6), the solver's net targeting income expression is obtained:

$$\max_{\{3,y,e_i,E_{ij}} cM = \frac{N\left(\left(2\{3x_0 + 2yx_0^2 - (\{3 + yx_0)^2\right) + N(N-1)(2yx_0^2 - y^2x_0^2)\right)}{2k} - \frac{1}{2}pa^2N\left(\{3^2 + Ny^2x_0^2\right) - N5 \qquad \textbf{(Apx\_B2-2)}$$

$$s.t. \frac{Nx_0(\{3 + Nyx_0)}{k} \geq Q$$

The Hessian matrix $_{cM} = \begin{vmatrix} -(\frac{N}{k} + Npa^2) & -\frac{Nx0}{k}) \\ -\frac{Nx_0}{k} & -(\frac{N^2x_0^2}{k} + N^2x_0^2pa^2) \end{vmatrix}$ is negative definite. Therefore, the Lagrange function is constructed under the constraint of retaining the task volume, which is

$$L(\{3, y) = \frac{N(2\{3x_0 + 2yx_0^2 - (\{3 + yx_0)^2) + N(N-1)(2yx_0^2 - y^2x_0^2)}{2k} - \frac{1}{2}pa^2N(\{3^2 + N_y^2x_0^2) - N5 - \lambda(Q - \frac{Nx_0(\{3 + Nyx_0)}{k}) \quad \textbf{(Apx\_B2-3)}$$

The Karush-Kuhn-Tucker (KKT) conditions (Gordan, G. and Tibshirani, R., 2012) are:

$$\frac{acM}{a\{3} = \frac{Nx_0(1 - y + \lambda)}{k} - \left(\frac{N}{k} + Npa^2\right)\{3 = 0 \quad \textbf{(Apx\_B2-4)}$$

$$\frac{acM}{ay} = \frac{Nx_0(Nx_0 - \{3 + \lambda x_0)}{k} - \left(\frac{N^2x_0^2}{k} + N^2x_0^2pa^2\right)y = 0 \quad \textbf{(Apx\_B2-5)}$$

$$\lambda(\frac{Nx_0(\{3 + Nyx_0)}{k} - Q) = 0, \lambda \geq 0 \quad \textbf{(Apx\_B2-6)}$$

Now discussion is made from the following two aspects:

(1) $\lambda = 0$

This situation indicates that the balanced total performance output of the crowdsourcing project is higher than the retained task volume, and the constraints do not work. By simultaneous Equations (Apx_B2- 4) and (Apx_B2- 5), the equilibrium individual performance reward coefficient and total performance reward coefficient are obtained as:

$$\{3^{R^*} = \frac{bx_0N}{(1+b)^2N - 1}, y^{R^*} = \frac{(1+b)N - 1}{(1+b)^2N - 1} \quad \textbf{(Apx\_B2-7)}$$

Substituting them back to (4.8), the expression of two types of balanced effort is:

$$e_i^{R^*} = \frac{((1+2b)N-1)x_0}{((1+b)^2N-1)k}, E_{ij}^{R^*} = \frac{((1+b)N-1)x_0}{((1+b)^2N-1)k} \tag{Apx\_B2-8}$$

And the expression of net income of the seeker is obtained:

$$cM^{R^*} = \frac{N^2x_0^2((1+b)^3N^2 + (1+b)(b^2-2)N + 1 - b)}{2k((1+b)^2N-1)^2} - N\delta \tag{Apx\_B2-9}$$

In this case, the condition that the retained task volume meets is: $Q < E(Y^{R*}) = \frac{N^2x_0^2(N-1+(N+1)b)}{((1+b)^2N-1)k}$, of which $b = kpa^2$ is called the risk factor, which is determined by the solver's risk preference coefficient and the uncertainty of performance output, which reflects the solver's perception of crowdsourcing risk.

(2) $\lambda > 0$

There must be $\frac{Nx0(\beta+N\gamma x0)}{k} - Q = 0$ in this case. It means that the performance of the solver is constrained by task volume. Substituting $\frac{Nx0(\beta+N\gamma x0)}{k} - Q = 0$ into Equations (Apx_B2-4) and (Apx_B2-5):

$$\beta^{R1^*} = \frac{((1+b)N-1)Qk - N^2(N-1)x_0^2}{Nx_0(2bN+N-1)},$$

$$\gamma^{R1^*} = \frac{bQk + N(N-1)x_0^2}{Nx_0^2(2bN+N-1)}, \tag{Apx\_B2-10}$$

$$\lambda = \frac{Qk((1+b)^2N-1) - N^2x_0^2(N-1+(N+1)b)}{Nx_0^2((1+2b)N-1)}$$

Because $\lambda > 0$, it isgot:

$$Q > \frac{N^2x_0^2(N-1+(N+1)b)}{((1+b)^2N-1)k} \tag{Apx\_B2-11}$$

Substituting Equations (Apx_B2-10) into (Apx_B2-1) the expressions of two types of the effort:

$$e_i^{R1^*} = \frac{((1+b)N + b - 1)\theta k - N(N-1)^2 x_0^2}{N x_0 (2bN + N - 1)k},$$

$$E_{ij}^{R1^*} = \frac{b\theta k + N(N-1)x_0^2}{N x_0 (2bN + N - 1)k}$$ **(Apx_B2- 12)**

The net income expression of the seeker is:

$$^{R1^*} = \theta - \frac{N((\beta^{R1*} + x_0 y^{R1*})^2 + (N-1)x_0^2 y^{R1*^2} + b(\beta^{R1*^2} + N x_0^2 y^{R1*^2}))cM}{2k} - N5$$ **(Apx_B2- 13)**

Justified.

2. Proof of Result 2

(1) When $\lambda = 0$, according to the expression of y^{R*}, $0 < y^{R*} < 1$ always holds. And from the condition of the establishment of the incentive mechanism which is $0 < \beta < 1$, getting $b x_0 N < (1+b)^2 N - 1$, further it canget that $x_0 < \frac{(1+b)^2 N - 1}{bN}$.

(2) When $\lambda > 0$, according to $0 < \beta < 1$ and $0 < y < 1$, getting $\theta < \frac{N x_0 (2bN + N - 1 + N x_0 (N-1))}{((1+b)N - 1)k}$ and $\theta < \frac{2N^2 x_0^2}{k}$. Because $\frac{N x_0 (2bN + N - 1 + N x_0 (N-1))}{((1+b)N - 1)k} < \frac{2N^2 x_0^2}{k}$ always holds in this condition, so it is sure to have $\theta < \frac{N x_0 (2bN + N - 1 + N x_0 (N-1))}{((1+b)N - 1)k}$.

Justified.

3. Proof of Result 3

According to the expressions of $e_i^{R^*}, E_{ij}^{R^*}, \beta^{R*}, y^{R*}$ and $e_i^{R1^*}, E_{ij}^{R1^*}, \beta^{R1*}, y^{R1*}$ (Table3-1), making the first-order partial derivatives of x_0, by judging the signs of the results, Result 3 is got.

4. Proof of Result 4

By taking the first-order partial derivatives from the expressions of $\beta^{R*}, y^{R*}, e_i^{R^*}, E_{ij}^{R^*}, cM^{R*}$, getting: (1) $\frac{\partial \beta^{R^*}}{\partial N} = \frac{-b x_0}{((1+b)^2 N - 1)^2} < 0$, $\frac{\partial y^{R^*}}{\partial N} = \frac{b(1+b)}{((1+b)^2 N - 1)^2} >$

$0, \frac{\partial e_i^{R^*}}{\partial N} = \frac{b^2 x_0}{((1+b)^2 N-1)^2 k} > 0, \frac{\partial E_{ij}^{R^*}}{\partial N} = \frac{b(1+b)x_0}{((1+b)^2 N-1)^2 k} > 0, \frac{\partial cM^{R^*}}{\partial N} = \frac{N(2(1+b)^3 N^2 + (1+b)b(b-4N) - 2(b-1))x_0^2}{2k((1+b)^2 N-1)^2} > 0.$

(2) Since $\frac{((1+b)N-1)\theta k}{N(2bN+N-1)x_0}$ is negatively related to N, $\frac{N^2(N-1)x_0}{N(2bN+N-1)}$ is positively related to N, so β^{R1*} is negatively related to N; $\frac{\partial y^{R1^*}}{\partial N} = \frac{2bN^2x_0^2 - (2(1+2b)N-1)b\theta k}{(Nx_0^2(2bN+N-1))^2} < \frac{2bN^2x_0^2 - \frac{(2(1+2b)N-1)}{1+b}bN^2x_0^2}{(Nx_0^2(2bN+N-1))^2} < 0$. From (Apx_B2-1), it can be seen that both $e_i^{R1^*}, E_{ij}^{R1^*}$ are negatively correlated to N.

Justified.

5. Proof of Result 5

(1) By taking the first-order partial derivatives of risk factor b from certain expressions, it is got :

$$\frac{\partial y^{R^*}}{\partial b} = \frac{-N^2b^2 - 2N(N-1)b - N(N-1)}{((1+b)^2 N-1)^2} < 0,$$

$$\frac{\partial \beta^{R^*}}{\partial b} = \frac{Nx_0(N-1-Nb^2)}{((1+b)^2 N-1)^2}, \frac{\partial E_{ij}^{R^*}}{\partial N} = \left[\frac{\partial y^{R^*}}{\partial b}\right]\frac{x_0}{k} < 0,$$

$$\frac{\partial e_i^{R^*}}{\partial N} = \frac{-2bNx_0(Nb+N-1)}{((1+b)^2 N-1)^2} < 0$$

(2) It can be seen from the conditions of Result 2 that $\theta k - 2N^2x_0^2 < 0$, so

$$\frac{\partial y^{R1^*}}{\partial b} = \frac{(N-1)(\theta k - 2N^2x_0^2)}{Nx_0^2(2bN+N-1)^2} < 0, \quad \frac{\partial \beta^{R1^*}}{\partial b} = \frac{(N-1)(2N^2x_0^2 - \theta k)}{x_0(2bN+N-1)^2} > 0,$$

$$\frac{\partial E_{ij}^{R1^*}}{\partial b} = \left[\frac{\partial y^{R1^*}}{\partial b}\right]\frac{x_0}{k} < 0, \frac{\partial e_i^{R1^*}}{\partial b} = \frac{(N-1)^2(2N^2x_0^2 - \theta k)}{Nx_0(2bN+N-1)^2 k} > 0$$

Justified.

6. Proof of Result 6

According to the expressions of $e_i^{NR^*}, \omega^{NR*}, \beta^{NR*}$ and $e_i^{NR1^*}, \omega^{NR1*}, \beta^{NR1*}$ in Table 3-1, making the first-order partial derivatives of x_0, b, N, θ, by judging the signs of the results, Result 6 is obtained.

7. Proof of Result 7

By using difference method, it isgot:

$$E\left(Y^{R^*}\right) > E\left(N^{R*}\right) > \frac{N x_0^2 b^2}{\left((1+b)^2 N - 1\right)(1+b)k} > 0,$$

$$\beta^{R^*} - \beta^{NR^*} = \frac{-\left((1+b)N-1\right)x_0}{\left((1+b)^2 N - 1\right)(1+b)} < 0,$$

$$e_i^{R^*} - e_i^{NR^*} = \frac{b\left((1+b)N-1\right)x_0}{\left((1+b)^2 N - 1\right)(1+b)k} \quad 0,$$

$$\beta^{R1^*} - \beta^{NR1^*} = \frac{-bN\theta k - N^2(N-1)x_0^2}{N x_0\left((1+2b)N-1\right)} < 0,$$

$$e_i^{R1^*} - e_i^{NR1^*} = \frac{-b(N-1)\theta k - N(N-1)^2 x_0^2}{N x_0\left((1+2b)N-1\right)k} < 0,$$

$$y^{R*} - y^{NR*} = y^{R*} > 0, E_{ij}^{R^*} - E_{ij}^{NR^*} = E_{ij}^{R^*} > 0,$$

$$y^{R1^*} - y^{NR1^*} = y^{R1^*} > 0, E_{ij}^{R1^*} - E_{ij}^{NR1^*} = E_{ij}^{R1^*} > 0$$

Justified.

B.2.2 Model Solving Process of Chapter 4

1. Equilibrium solution of task Stage 2

Similar to B.2.1, the incentive constraint (IC) in Equation (4-13) is first solved. Taking the first-order partial derivative of constraint (IC) with respective to e_2, it is got $k(n-1)\frac{2^{n-1}(_2\, 0(\ ))^{n-2}}{n} h_2(0)\{3_2(ke_2+v)+k\{3_2\frac{2^{n-1}(_t\, 0(\ ))^{n-1}}{n}-\frac{u}{<f}e_2=0$, so the optimal effort level of each solver in the second task phase is

$$e_2=\frac{<fk(a_2+v(n-1))\{3_2}{na_2u-<fk^2(n-1)\{3_2} \qquad \textbf{(Apx\_B2-14)}$$

$a_2=\sqrt{2(\lambda^2 r a_y^2+a_\varepsilon^2)\mathcal{T}}$. It can be seen that the Hessian is negative only when the condition $\{3_2<\frac{na2u}{(n-1)<fk^2}$ is satisfied, and the equilibrium solution can be obtained.

Then considering constraint (IR) in Equation (4- 13). Obviously, a rational seeker will allow the solver to obtain a deterministic benefit higher than the retained utility, so taking the equal sign in (IR). F_{i2} is the retained utility of the solver i in the second task stage, and obviously there is $F_{12}=F_{22}=...=F_{n2}=F_2$. The retained utility is the maximum utility that the solver may gain by participating in the task at the expense of giving up other opportunities. And in the reputation incentive mechanism, the retained utility is related to its bargaining ability with the seeker, so there is $F_2=\ _2=\frac{1(U2+n\ 2)}{n}$, 1 represents the bargaining ability of the solver. Substituting the expression of a_2 obtained from the (IR) constraint and Equation (Apx_B2- 14) into U_2, the economic benefit of the seeker is:

$$U_2=(1-1)\left[\left(\frac{<fk(a_2+v(n-1))\{3_2}{na_2u-<fk^2(n-1)\{3_2}+v\right)-\frac{nu}{2<1}\left(\frac{<fk(a_2+v(n-1))\{3_2}{na_2u-<fk^2(n-1)\{3_2}\right)^2\right] \qquad \textbf{(Apx\_B2-15)}$$

The $\{3_2^*$ is obtained by the first-order partial derivative of U_2, then substituting $\{3_2^*$ into Equation (Apx_B2-14), it is got:

$$\{3_2^* = \frac{na_2u}{na_2u + (n-1)(nuv + k^2<f)}, e_2^* = \frac{k<f}{nu} \quad \textbf{(Apx\_B2-16)}$$

It is found that $\{3_2 < \frac{na2u}{<fk^2(n-1)}$ is always established. Therefore, the equilibrium solution of the model must exist. So, the optimal fixed reward of the solver in the second task phase is:

$$a_2^* = \frac{n1 - \{3_2^*}{n}(ke_2 + v) - \frac{u(n1-1)}{2<f} e_2^{*2} \quad \textbf{(Apx\_B2-17)}$$

The deterministic benefits of the seeker and each solver are:

$$U_2^* = (1 - 1)\left(\frac{k^2<t}{2nu} + v\right), \quad {}_2^* = \frac{1}{n}\left(\frac{k^2<t}{2nu} + v\right) \quad \textbf{(Apx\_B2-18)}$$

2. Equilibrium solution of task Stage 1

Substituting the $v_i = (1 - r)\lambda a + r(m_{i1} - ke_{i1}^*)$ of Equation (4-2) into constraint (IC) in Equation (4- 14) and taking the first-order partial derivative of (IC) with respective to e_{i1}, it is got:

$$\frac{2k(n-1)}{n}\frac{1}{2\sqrt{2(\lambda^2 a_y^2 + a_E^2)\mathcal{L}}}\left(\{3_1 ke_1 + \lambda a\right) + \frac{k\{3_1}{n} - \frac{u}{<f}e_1 - \frac{\{3_2 kr}{n} = 0 \quad \textbf{(Apx\_B2-19)}$$

Obviously, the Hessian matrix is negatively definite. The optimal e_1^* is:

$$e_1^* = \frac{<fk((a_1 + n(-1)\lambda a)\{3_1 - ra_1\{3_2)}{na_1u - <fk^2(n-1)\{3_1} \quad \textbf{(Apx\_B2-20)}$$

$a_1 = \sqrt{2(\lambda^2 a_y^2 + a_E^2)\mathcal{L}}$. Then letting constraint (IR) in Equation (4-14) take the equal sign, the expression of $a_1 + a_2$ is got, and by substituting $a_1 + a_2$ into the objective function of the seeker, it is got:

$$\max_{\{3_1} U = ke_1(\{3_1 + \lambda a) - \frac{nu}{2<f}e_1\{3_1^2 + (ke_2 + (1-r)\lambda a + r(m_1 - ke_1\{3_1)) - \frac{nu}{2<f}e_2^2$$

$$- \sum_{i=1}^{n} F_i \quad \textbf{(Apx\_B2-21)}$$

Substituting the expression of e_1^* in Equations (Apx_B2-20) into (Apx_B2-21), and then taking the first-order partial derivative of U with respective to $\{3_1$, the expression of $\{3_1^*$ is got, and then substitute it into Equation (Apx_B2- 20), the optimal effort of the solver is obtained:

$$\{3_1^* = \frac{na_1u(r\{3_2^* + (1-r))}{na_1u + (n-1)(nu\lambda a + (1-r)k^2<f)}, e_1^* = \frac{k<f(1-r)}{nu} \quad \textbf{(Apx\_B2-22)}$$

The economic benefits of the seeker in Stage 1 is:

$$U_1^* = \left(\frac{k^2<f(1-r)(1+r)}{2nu} + \lambda a\right) + 1\left(\frac{k^2<f}{2nu} + v\right) - \boldsymbol{L}_{i=1}^{n} F_i \quad \textbf{(Apx\_B2-23)}$$

3. Proof of Result 1

From Table 4-1, it is got:

$$_2 = w_2 = a_2 + \frac{2^{n-1}\left(_2 \quad \left(k\left(e_{i2} - e_{j2}\right)\right)\right)^{n-1}}{n} \{3_2 m_2,$$

$$\frac{a\{3_2^*}{av} = \frac{-(n-1)n^2a_2u^2}{\left(na_2u + (n-1)(nuv + k^2<f)\right)^2} < 0,$$

$$\frac{aa_2^*}{av} = n1 - \{3_2^* - \frac{a\{3_2^*}{av}(ke_2 + v) = n1 - \left(\{3_2^* + \frac{a\{3_2^*}{av}(ke_2 + v)\right)$$

$$= n1 - \frac{n^2a_2^2u^2}{\left(na_2u + (n-1)(nuv + k^2<f)\right)^2},$$

$$x(n) = \frac{a_2^2u^2}{n(a_2u + uv(n-1) + k^2<f(1-\frac{1}{n}))^2}, \frac{ax(n)}{an} < 0$$

Justified.

4. Proof of Result 2

By finding the derivations of e_1^* in Table 4-1 with respective to $\{3_1^*$ and $\{3_2^*$, Result 2 is obtained.

5. Proof of Result 3

By taking the derivatives of $e^*_2, \{3^*_2, e^*_1, \{3^*_1$ in Table 4-1 with respective to $<f$, it is got:

$$\frac{a\{3^*_2}{a<f} = \frac{-n(n-1)a_2uk^2}{\left(na_2u + (n-1)(nuv + k^2<f)\right)} \le 0, \quad \frac{ae^*_2}{a<f} = \frac{k}{nu} > 0,$$

$$\frac{a\{3^*_1}{a<f} = \frac{-n(n-1)a_1u\left(r\{3^*_2 + (1-r)\right)(1-r)k^2}{\left(na_1u + (n-1)(nu\lambda a + (1-r)k^2<f)\right)} \le 0, \quad \frac{ae^*_1}{a<f} = \frac{k(1-r)}{nu} > 0$$

Justified.

6. Proof of Result 4

By taking the derivatives of $e^*_2, \{3^*_2, e^*_1, \{3^*_1$ in Table 4-1 with respective to r, it is got:

$$\frac{a\{3^*_2}{ar} = \frac{a\{3^*_2}{aa_2}\frac{aa_2}{ar} = \frac{2\lambda^2 a_y^2 n(n-1)(nuv + k^2<f)u}{2\sqrt{2(\lambda^2 r a_y^2 + a_\varepsilon^2)}\,\lambda\left(na_2u + (n-1)(nuv + k^2<f)\right)^2} \ge 0,$$

$$\frac{ae^*_2}{ar} = 0,$$

$$\frac{a\{3^*_1}{ar} < \frac{-na_1u(na_1u + (n-1)nu\lambda a - r(na_1u + (n-1)(nu\lambda a + (1-r)k^2<f)))}{\left(na_1u + (n-1)(nu\lambda a + (1-r)k^2<f)\right)^2} < 0,$$

$$\frac{ae^*_1}{ar} = \frac{-k<f}{nu} < 0$$

Justified.

7. Proof of Result 5

By taking the derivatives of $e^*_2, \{3^*_2, e^*_1, \{3^*_1$ in Table 4-1 with respective to n, Result 5 is got.

8. Proof of Result 6

By taking the derivatives of U^*_1 and U^*_2 in Table 4-1 with respective to $r, <f, n$, Result 6 is got.

9. Proof of Result 7

By difference method, it is got:

$$\{3^*_0 - \{3^*_2 = \frac{uk^2(a_1 <f - a_2) + nu^2 a_1 v}{\left(a_2 u + \left(1 - \frac{1}{n}\right)(nuv + k^2 <f)\right)\left(\left(1 - \frac{1}{n-1}\right) a_1 u + k^2\right)} > 0,$$

$$\frac{a(\{3^*_0 - \{3^*_2)}{an} < 0, \; e^*_2 - e^*_0 = \frac{k(<f - 1)}{nu} > 0, \; \frac{a(e^*_2 - e^*_0)}{an} < 0$$

Justified.

10. Proof of Result 8

By difference method similar to Result 7, Result 8 is got.

B.2.3 Model Solving Process of Chapter 5

1. Equilibrium solution of NKS model

Taking the derivatives of U_i in Equation (5- 8) with respective to e_i, s_i, it is got:

$$\frac{\partial U_i}{\partial e_i}=\frac{(n-1)1\left((n-1)\lambda+1\right)A}{e_i u n^2}-\left((n-1)\lambda+1\right)c_e+\frac{(n-1)1\lambda A}{e_i u n^2}=0,$$
$$\frac{\partial U_i}{\partial s_i}=\left((n-1)\lambda+1\right)\left(\frac{kc_e}{n}-hs_i\right)-\lambda\frac{(n-1)kc_e}{n}=0 \qquad \textbf{(Apx\_B2- 24)}$$

Then:

$$e_i^{NK5^*}=\frac{A(n-1)1(1\lambda+1)}{uc_e n^2\left((n-1)\lambda+1\right)},\ s_i^{NK5^*}=\frac{kc_e}{((n-1)\lambda+1)nh} \qquad \textbf{(Apx\_B2- 25)}$$

Hence, $\frac{\partial^2 U_i}{\partial e_i^2}=-\frac{(n-1)(n\lambda+1)A}{e_i^2 u n^2}<0$, $\frac{\partial^2 U_i}{\partial s_i^2}=-h\left((n-1)\lambda+1\right)<0$, and it can be seen that the Hessian matrix is negatively definite, so $e_i^{NK5^*}$ and $s_i^{NK5^*}$ are the optimal action plans of the solver. Substituting Equation (Apx_B2- 25) into Equations (5- 4), (5- 5), the economic benefit expressions of the seeker and the solver is obtained, which are:

$$\pi_i^{NK5^*}=\frac{k^2c_e^2\left(2n\left((n-1)\lambda+1\right)-1\right)}{2n^2h((n-1)\lambda+1)^2}+\frac{A}{n}\left(1-\frac{(n\lambda+1)(n-1)1}{((n-1)\lambda+1)nu}\right) \qquad \textbf{(Apx\_B2- 26)}$$

$$^{NK5*}=(1\ln e+\beta s_i)-A=1\ln\left(\frac{A(n-1)1(1\lambda+1)}{uc_e n^2\left((n-1)\lambda+1\right)}\right)+\frac{\beta kc_e}{\left((n-1)\lambda+1\right)nh}-A \qquad \textbf{(Apx\_B2- 27)}$$

The task performance is:

$$E(y^{NK5^*})=1\ln\left(\frac{A(n-1)1(1\lambda+1)}{uc_e n^2\left((n-1)\lambda+1\right)}\right)+\frac{\beta kc_e}{\left((n-1)\lambda+1\right)nh} \qquad \textbf{(Apx\_B2- 28)}$$

2. Equilibrium solution of KS model

Firstly, finding the first-order partial derivatives of U_i in Equation (5- 8) with respective to e_i, s_i, and making them equal 0. Then substituting the symmetrical strategies $e=e_i=e^*$ and $s=s_i=s^*$ into the derivatives, doing the Hessian matrix negative definite test of which the result is passed, so the optimal e_i, s_i under the KS mechanism are as follows:

$$e_i^{K5^*} = \frac{A(n-1)1(n\lambda+1)}{uc_e n^2\left((n-1)\lambda+1\right)},\ s_i^{K5^*}(b) = \frac{\left((n-1)\lambda+1\right)nbe+kc_e}{\left((n-1)\lambda+1\right)nh} \quad \textbf{(Apx\_B2-29)}$$

Substituting Equation (Apx_B2-29) into Equation (5-4), the expression of the economic benefit of the seeker with respect to the incentive degree b is:

$$\begin{aligned}(b) &= \sum_{i=1}^{n} \frac{1\ln\left(\frac{A(n-1)1(n\lambda+1)}{uc_e n^2\left((n-1)\lambda+1\right)}\right)+\beta\left(\frac{\left((n-1)\lambda+1\right)nbe+kc_e}{\left((n-1)\lambda+1\right)nh}\right)}{n} \\ &\quad - A - \sum_{i=1}^{n} be\left(\frac{\left((n-1)\lambda+1\right)nbe+kc_e}{\left((n-1)\lambda+1\right)nh}\right) \\ &= 1\ln\left(\frac{A(n-1)1(n\lambda+1)}{uc_e n^2\left((n-1)\lambda+1\right)}\right)+\frac{\beta kc_e}{\left((n-1)\lambda+1\right)nh} \\ &\quad + \frac{\left(\left((n-1)\lambda+1\right)\beta-kc_e\right)e}{\left((n-1)\lambda+1\right)h}b-\frac{ne^2}{h}b^2-A\end{aligned} \quad \textbf{(Apx\_B2-30)}$$

Because $\frac{a^2}{ab^2}<0$, andby setting the first-order partial derivative of with respective to b equalling 0, so (b) is a convex function with respective to b, and the seeker should decide the optimal degree of knowledge sharing incentive b. Finding the first-order partial derivative of (b) with respective to b, and taking the equal sign, the expression of b^{K5*} is got. And then substituting it into Equation (Apx_B2-29), the expression of $s_i^{K5^*}$ is obtained:

$$b^{K5^*} = \frac{\left((n-1)\lambda+1\right)\beta-kc_e}{2n\left((n-1)\lambda+1\right)e},\ s_i^{K5^*} = \frac{\left((n-1)\lambda+1\right)\beta+kc_e}{2\left((n-1)\lambda+1\right)nh} \quad \textbf{(Apx\_B2-31)}$$

Further, the expressions of economic benefit of the solver i and the seeker are:

$$\begin{aligned}\pi_i^{K5^*} &= \frac{\left(\left((n-1)\lambda+1\right)\beta+kc_e\right)\left(\left((n-1)\lambda+1\right)\beta+\left(4n(n-1)\lambda+4n-3\right)kc_e\right)}{8n^2h\left((n-1)\lambda+1\right)^2} \\ &\quad + \frac{A}{n}\left(1-\frac{(n\lambda+1)(n-1)1}{\left((n-1)\lambda+1\right)nu}\right) \\ {}^{K5^*} &= 1\ln\left(\frac{A(n-1)1(n\lambda+1)}{uc_e n^2\left((n-1)\lambda+1\right)}\right)+\frac{\left(\left((n-1)\lambda+1\right)\beta+kc_e\right)^2}{4nh\left((n-1)\lambda+1\right)^2}-A\end{aligned} \quad \textbf{(Apx\_B2-32)}$$

The task performance stimulated by knowledge sharing is as follows:

$$E(v^{K5^*}) = 1\ln\left(\frac{A(n-1)1(1\lambda+1)}{uc_e n^2((n-1)\lambda+1)}\right) + \frac{(((n-1)\lambda+1)\beta+kc_e)\beta}{2((n-1)\lambda+1)nh} \quad \textbf{(Apx\_B2-33)}$$

3. Proof of Result 1

From the expression of b^{K5^*} in Table 5-1 and the condition $b^{K5^*} > 0$, it is got $\beta > \frac{kc_e}{(n-1)\lambda+1} = \delta_0(\lambda)$, obviously $\frac{\partial\delta_0(\lambda)}{\partial\lambda} = \frac{-(n-1)kc_e}{((n-1)\lambda+1)^2} < 0$.

Justified.

4. Proof of Result 2

Finding the first-order partial derivatives of b^{K5^*} in Table 5-1 with respective to λ, β, k, e, n, it is got:

$$b^{K5^*} = \frac{((n-1)\lambda+1)\beta - kc_e}{2n((n-1)\lambda+1)e}, \frac{\partial b^{K5^*}}{\partial\lambda} = \frac{kc_e(n-1)}{2ne((n-1)\lambda+1)^2} > 0,$$

$$\frac{\partial b^{K5^*}}{\partial\beta} = \frac{1}{2ne} > 0, \frac{\partial b^{K5^*}}{\partial k} = \frac{-c_e}{2n((n-1)\lambda+1)e} < 0,$$

$$\frac{\partial b^{K5^*}}{\partial e} = -\frac{((n-1)\lambda+1)\beta - kc_e}{2n((n-1)\lambda+1)e^2} < 0, \frac{\partial b^{K5^*}}{\partial n} = -\frac{1}{2ne}\left(\frac{\beta}{n} - \frac{k\lambda c_e}{((n-1)\lambda+1)^2}\right) < 0$$

Justified.

5. Proof of Result 3

From Table 5-1, it can be easily found that $e_i^{NK5^*} = e_i^{K5^*}$. Finding first-order derivates of $e_i^{K5^*}$ with respective to λ and n, it is got:

$$\frac{\partial e_i^{K5^*}}{\partial\lambda} = \frac{\partial e_i^{NK5^*}}{\partial\lambda} = \frac{A(n-1)1}{uc_e n^2((n-1)\lambda+1)^2} > 0,$$

$$\frac{\partial e_i^{K5^*}}{\partial n} = \frac{\partial e_i^{NK5^*}}{\partial n} = \frac{A1}{uc_e}\left(-\frac{n^2-1}{n^4} - \frac{(n\lambda+1)}{((n-1)\lambda+1)} - \frac{n-1}{n^2}\frac{\lambda^2}{((n-1)\lambda+1)^2}\right) < 0$$

Justified.

6. Proof of Result 4

From Table 5-1, finding first-order derivatives of $s_i^{K5^*}$ and $s_i^{NK5^*}$ with respective to λ and n, and then substituting the condition $\left((n-1)\lambda+1\right)\{3-kc_e>0$ which is obtained in Result 1 into the derivatives, it is got:

$$\frac{\partial s_i^{NK5^*}}{\partial\lambda}=-\frac{(n-1)nhkc_e}{\left((n-1)\lambda+1\right)^2 n^2h^2}<0,\quad \frac{\partial s_i^{NK5^*}}{\partial n}=-\frac{(2n\lambda+1-\lambda)kc_e}{\left((n-1)\lambda+1\right)^2 n^2h^2}<0,$$

$$\frac{\partial s_i^{K5^*}}{\partial\lambda}=-\frac{(n-1)kc_e}{2\left((n-1)\lambda+1\right)^2 nh}<0,\quad \frac{\partial s_i^{K5^*}}{\partial n}=-\frac{(2n\lambda+1-\lambda)kc_e}{2\left((n-1)\lambda+1\right)^2 n^2h^2}<0,$$

$$\frac{\partial s_i^{K5^*}}{\partial e}=0,\quad s_i^{K5^*}-s_i^{NK5^*}=\frac{\left((n-1)\lambda+1\right)\{3-kc_e}{2\left((n-1)\lambda+1\right)nh}>0,$$

$$\frac{\partial(s_i^{K5^*}-s_i^{NK5^*})}{\partial\lambda}=\frac{(n-1)nhkc_e}{2\left((n-1)\lambda+1\right)^2 n^2h^2}>0$$

Justified.

7. Proof of Result 5

From Table 5-1, it is got:

$$\frac{\partial E\left(v^{NK5^*}\right)}{\partial\lambda}=\frac{1nh\left((n-1)\lambda+1\right)-\{3kc_e(n-1)(n\lambda+1)}{nh(n\lambda+1)\left((n-1)\lambda+1\right)^2},$$

$$\frac{\partial E\left(v^{K5^*}\right)}{\partial\lambda}=\frac{1nh\left((n-1)\lambda+1\right)-\{3kc_e(n-1)(n\lambda+1)}{2nh(n\lambda+1)\left((n-1)\lambda+1\right)^2},$$

$$E\left(v^{K5^*}\right)-E\left(v^{NK5^*}\right)=\frac{\{3\left(\left((n-1)\lambda+1\right)\{3-kc_e\right)}{2\left((n-1)\lambda+1\right)nh}>0,$$

$$\frac{\partial(E\left(v^{K5^*}\right)-E\left(v^{NK5^*}\right))}{\partial\lambda}=\frac{\{3kc_e(n-1)}{2\left((n-1)\lambda+1\right)^2 nh^2}>0$$

Solving the equations $\frac{aE\left(v^{NK5^*}\right)}{a\lambda} = 0$ and $\frac{aE\left(v^{K5^*}\right)}{a\lambda} = 0$ with respective to λ, then $\frac{1}{\{3k} = \frac{c_e(n-1)(n\lambda+1)}{hn((n-1)\lambda+1)}$. Obviously $\frac{1}{\{3k}$ is a monotonically increasing function with respective to λ. Substituting $0 < \lambda < 1$ to $\frac{1}{\{3k}$, findings (1) and (2) in Result 5 are obtained. Justified.

8. Proof of Result 6

According to Table 5-1, it is got:

$$\frac{a^{K5^*}}{a\lambda} = \frac{21nh((n-1)\lambda+1) - \{3kc_e(n-1)(n\lambda+1)}{2nh(n\lambda+1)((n-1)\lambda+1)^2} - \frac{\frac{(n-1)k^2c_e^2}{(n\lambda+1)((n-1)\lambda+1)}}{2nh((n-1)\lambda+1)^2}$$

$$^{K5^*} - {}^{NK5^*} = \frac{(((n-1)\lambda+1)\{3-kc_e)^2}{4nh((n-1)\lambda+1)^2} > 0$$

$$\frac{a(^{K5*} - {}^{NK5*})}{a\lambda} = \frac{(((n-1)\lambda+1)\{3-kc_e)(n-1)kc_e}{2nh((n-1)\lambda+1)^3} > 0$$

By taking $\lambda = 0$ and $\lambda = 1$, it is easy to tell the sign of $\frac{a^{NK5^*}}{a\lambda}$ and $\frac{a^{K5^*}}{a\lambda}$.

Justified.

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Appendix C The Screenshots of Web Crawling Program in Chapter 6

C.1 The Screenshots of Web Crawling Program in Python 3.7

C.1.1 Screenshots of Data Crawling Program

```
获取任务列表taskList.py

import time
from random import randint
from retrying import retry
from multiprocessing.dummy import Pool as ThreadPool
from lxml import etree
from datetime import datetime
import requests
from pymongo import MongoClient

db = {'host': 'localhost', 'port': 27017, 'db':'db', 'collection': 'taskzbj'}
conn = MongoClient(host=db['host'], port=db['port'])
conn1 = conn.get_database(db['db'])
conn = conn1.get_collection(db['collection'])
proxy_conn = conn1.get_collection("Proxy")

headers = {
    'Connection': 'keep-alive',
    'Pragma': 'no-cache',
    'Cache-Control': 'no-cache',
    'Upgrade-Insecure-Requests': '1',
    'User-Agent': 'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/87.0.4280.88 Safari/537.36',
    'Accept': 'text/html,application/xhtml+xml,application/xml;q=0.9,image/avif,image/webp,image/apng,*/*;q=0.8,application/signed-exchange;v=b3;q=0.9',
    'Sec-Fetch-Site': 'same-origin',
    'Sec-Fetch-Mode': 'navigate',
    'Sec-Fetch-User': '?1',
    'Sec-Fetch-Dest': 'document',
```

Figure_Apx C- 1 Data crawling program (Part 1)

```python
        'Referer': 'https://task.zbj.com/t-dsyxfwzbj/?so=2'&ss=0',
        'Accept-Language': 'zh-CN,zh;q=0.9',
}

params = (
    ('so', '2'),
    ('ss', '0'),
)

def datetime_2_str():
    now = datetime.now()
    date = now.strftime('%Y-%m-%d')
    return date

def proxy_count_all():
    return proxy_conn.iter().count()

def random_proxies():
    '''
    随机取出存储的proxies
    '''
    one_proxy = list(proxy_conn.aggregate([{ "$sample": { "size": 1 } }]))
    # print(type(one_proxy[0]))
    return one_proxy[0]

def get_proxy():
```

Figure_Apx C- 2 Data crawling program (Part 2)

```python
    return random_proxies()


def increase_proxy(one_ip):
    proxy_conn.update_one({
        '_id': one_ip['_id'],
        "ip": one_ip["ip"],
        "time": one_ip["time"]
    }, {
        '$inc': {
            'score': -1,
        }})
    print(f"{one_ip['ip']}扣除一分！")


def wait(attempts, delay):
    print('Attempt #%d, retrying in %d seconds' % (attempts, delay // 1000))
    return delay

@retry(stop_max_attempt_number=3, wait_random_min=1000, wait_random_max=2000,wait_func=wait)
def getOnePage(page):
    one_proxy = get_proxy()
    proxies= one_proxy["ip"]
    proxies = {'https': proxies}
    response = requests.get(f"https://task.zbj.com/page{page}.html/", headers=headers, proxies=proxies,params=params,timeout=(3,5))
    html = etree.HTML(response.text)
    now_day = datetime_2_str()
```

Figure_Apx C- 3 Data crawling program (Part 3)

```python
cards = html.xpath("//div[@class='demand-list']/div[@class='demand-card']")
for card in cards:
    try:
        publisher = card.xpath('.//i[@class="encrypted-buyer-name"]/text()')
        publisher = publisher[0] if publisher else publisher
        try:
            publish_time = card.xpath('.//span[@class="card-pub-time flt"]/text()')[1].strip().replace("发布", "")
        except:
            publish_time = ""

        if "小时" in publish_time:
            publish_time = now_day

        try:
            participants = card.xpath('.//span[@class="card-pub-left frt"]/text()')[0].strip()
        except:
            participants = ""

        try:
            title = card.xpath('.//span[contains(@class, "demand-title")]//text()')[0].strip()
        except:
            title = ""

        try:
            tags = "|".join(card.xpath('.//span[@class="demand-tags"]/i/text()'))
        except:
            tags = ""
```

Figure_Apx C- 4 Data crawling program (Part 4)

```python

        try:
            demand_mode = card.xpath('.//span[@class="demand-mode"]/i/text()')[0]
        except:
            demand_mode = ""

        try:
            price = "".join(card.xpath(".//div[@class='demand-price']/text()")).strip()
        except:
            price = ""

        try:
            status = card.xpath(".//div[@class='demand-price']/span/text()")[0].strip()
        except:
            status = ""

        try:
            describe = card.xpath('.//div[@class="demand-card-desc"]/text()')[0]
        except:
            describe = ""

        try:
            taskID = card.xpath('.//div[@class="demand-card-foot"]/@data-link')[0].split("/")[-2]
        except:
            taskID = ""

        try:
```

Figure_Apx C- 5 Data crawling program (Part 5)

```python
                cate_and_region = card.xpath('.//div[@class="demand-foot-tags flt"]/span/text()')
                cate = cate_and_region[0]
                region = ""
                if len(cate_and_region) == 2:
                    region = cate_and_region[1]
            except:
                cate = ""
                region = ""

            taskData = {
                "id":taskID,
                "title":title,
                "publisher":publisher,
                "publish_time":publish_time,
                "participants":participants,
                "cate":cate,
                "region":region,
                "describe":describe,
                "status":status,
                "price":price,
                "demand_mode":demand_mode,
                "tags":tags,
            }
            conn.insert_one(taskData)
        except:
            print("error")
            pass
```

Figure_Apx C- 6 Data crawling program (Part 6)

```python

def try_get_one_page(page):
    try:
        getOnePage(page)
    except:
        pass

pageList = [i for i in range(1,21154)]

zbj_pool = ThreadPool(30)
zbj_pool.map(try_get_one_page, pageList)
zbj_pool.close()
zbj_pool.join()
```

Figure_Apx C- 7 Data crawling program (Part 7)

C.1.2 Screenshots of Data Output Program

数据导出outData.py

```python
import pandas as pd

data = pd.read_csv("zbjtaskList.csv")
data.to_excel("zbjtaskList.xlsx",encoding="utf-8",index=False)
```

Figure_Apx C- 8 Data output program

C.1.3 Screenshots of Data Cleaning Program

数据清洗data clean.py

```python
import pandas as pd
from pymongo import MongoClient
import matplotlib.pyplot as plt

def _connect_mongo(host, port, db):
    """ A util for making a connection to mongo """
    conn = MongoClient(host, port)
    return conn[db]


def read_mongo(db, collection, query={}, host='localhost', port=27017, no_id=True):
    """ Read from Mongo and Store into DataFrame """

    # Connect to MongoDB
    db = _connect_mongo(host=host, port=port, db=db)

    # Make a query to the specific DB and Collection
    cursor = db[collection].find(query)

    # Expand the cursor and construct the DataFrame
    df = pd.DataFrame(list(cursor),columns=["publish_time","participants","cate","status","price","demand_mode","id"])

    return df

data = read_mongo("db","taskzbj")
print(data.info())
data["publish_time"] = data["publish_time"].apply(lambda x:"2020-12-17" if "分钟前" in x else x)
```

Figure_Apx C- 9 Data cleaning program (Part 1)

```python
data["date"] = pd.to_datetime(data["publish_time"])
data["year"] = data["date"].dt.year
del data["publish_time"]
del data["date"]

data["participant_num"] = data["participants"].str.extract('(.*?) 人参与')
del data["participants"]
# data.dropna(axis=0,how='any',inplace=True)
print(data.info())
data.year = data.year.fillna(method='ffill')
data["year"] = data.year.astype("int16")
data.to_csv("zbjtaskList.csv",index=False)
# year_group = data.groupby("year").count()
# year_group.plot()

# plt.show()
```

Figure_Apx C- 10 Data cleaning program (Part 2)

Appendix D Glossary of Specific Terms

Backward induction: the process of reasoning backwards in time, from the end of a problem or situation, to determine a sequence of optimal actions

Benefit equivalent: the amount of benefit determined by positive utility

Click farm: a form of click fraud, where a large group of low-paid workers are hired to click on paid advertising links for the click fraudster

Convenience sampling: a type of non-probability sampling that involves the sample being drawn from that part of the population that is close to hand

Cost equivalent: the amount of benefit determined by negative utility

Deterministic equivalent return: the difference between expected return and risk premium

Empirical research: a type of research methodology that makes use of verifiable evidence in order to arrive at research outcomes

Free riding: a wide range of situations in which users of services do not pay for them, including fare evasion

Game theory: the study of mathematical models of strategic interaction among rational decision-makers

Gumbel distribution: an extreme value distribution to model the distribution of the maximum of a number of samples of various distributions

Individual rationality constraints (IR): a necessary condition for an economic agent to make a decision is that the decision gives the agent positive surplus

Incentive compatibility constraints (IC): a kind of institutional arrangement makes the pursuit of individual interests coincide with the enterprise's goal of maximising collective value

Mobile crowdsourcing: crowdsourcing activities that are processed on smartphones or other mobile devices**Principal-agent theory:** theory used to study on the principal-agent problem which is a conflict in priorities between a person or a group and the representative authorized to act for them

Repeated game: an extensive form game that consists of a number of repetitions of some base game (called a stage game) in game theory

Ratchet effect: an instance of the restrained ability of human processes to be reversed once a specific thing has happened, analogous with the mechanical ratchet that holds the spring tight as a clock is wound up. In principal-agent relationship, ratchet effect means the higher the incentive amount, the higher the requirement of the principal

Signalling game: a simple type of a dynamic Bayesian game. The essence of a signalling game is that one player takes an action, the signal, to convey information to another player, where sending the signal is more costly if they are conveying false information

Social theory: ideas, arguments, hypotheses, thought-experiments and explanatory speculations used to study and interpret social phenomena

Static game: a game where each player chooses their action without knowledge of the actions chosen by other players in game theory

Structural equation modelling: a multivariate statistical analysis technique that is used to analyse structural relationships

Synergistic incentive effect: originated from economics of scope, economics of scale, refers to the effect caused when exposure to two or more incentives at one time results in incentive effects that are greater than the sum of the effects of the individual incentive

Web crawler: an Internet bot that systematically browses the World Wide Web, typically operated by search engines for the purpose of Web indexing