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RESEARCH PAPER

Innovation Crowdsourcing Mechanisms and Innovation Performance: An Empirical Study of a Business Intelligence Community

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ABSTRACT

PURPOSE: This study aims to develop a research model to investigate how the structure and mechanisms of innovation crowdsourcing influence knowledge management and innovation performance, based on the perspectives of open innovation theory and the knowledge-based view (KBV) of the firm.

DESIGN/METHODOLOGY/APPROACH: The research model and associated hypotheses were tested using partial least squares structural equation modelling (PLS-SEM) based on a dataset from the Microsoft Power BI community of business intelligence (BI) and analytics tools.

FINDINGS: The results show that both organisational and technical mechanisms of the community positively influence the community structure. The community structure has a positive impact on knowledge acquisition, knowledge transformation and the size and diversity of crowd participation. The mechanisms of innovation crowdsourcing and knowledge transformation in turn have a strong influence on innovation performance.

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ORIGINALITY: This study is among the first to provide analytical insights into the mechanisms of innovation crowdsourcing and their underlying impact on innovation performance in the context of BI and analytics tools that exhibit a multiplicity and complexity of functions and capabilities. It therefore provides strategic guidance on how to effectively stimulate crowd intelligence and maximise the collaborative and synergistic effectiveness of innovation crowdsourcing communities, focusing on knowledge management practices and user innovation behaviour and performance.

KEYWORDS: *Innovation Crowdsourcing Communities; Innovation Performance; Knowledge Management; Crowdsourcing Mechanisms; Structural Equation Modelling (SEM); Business Intelligence (BI)*

INTRODUCTION

To achieve superior business performance through innovation, companies need to unleash their innovation and knowledge streams to drive new growth, and openly leverage untapped external knowledge to unlock new revenue and business opportunities. Today, innovation crowdsourcing communities are increasingly used to lead companies to breakthrough business advances and transformations (Chesbrough, 2019). Thanks to technological leaps, it is now possible for companies to tap into the collective intelligence of online crowds to expand their innovation capabilities and portfolios (Cheng *et al*., 2020). As a result, an increasing number of companies are outsourcing the process of generating and evaluating innovations and new ideas to online crowds from diverse backgrounds to mitigate the risk of sticking to the known and to overcome traditional product and service development by R&D departments (Daradkeh, 2021b). Innovation crowdsourcing communities, such as the Microsoft Power BI community, Tableau community and Qlik community, serve as intermediaries to bring out new innovations and solutions from the crowd of experts, customers, developers and technical evangelists for business intelligence (BI) and analytics technologies and tools (Daradkeh, 2021c).

The extant research on innovation crowdsourcing has emphasised the value of using online communities to develop, redesign, validate and ultimately sustain innovative ideas and solutions (Boon and Edler, 2018). Therefore, various crowdsourcing mechanisms have been advocated to shape and improve the process and quality of innovation. These mechanisms include the use of social networks that allow users to communicate and share interests and/or activities, the formation of collaborative groups that allow idea generators to easily develop their own ideas and create solutions together, and finally the organisation of ideation activities that include a mix of individual and various collaborative groups (Liu *et al*., 2020a). In most cases, however, simply creating new innovations is not enough to achieve successful innovation crowdsourcing outcomes. Moreover, innovation crowdsourcing is usually the first phase of an innovation crowdsourcing process. Collaborative innovation crowdsourcing also requires continuous crowd engagement to refine and improve already created innovations and to identify innovative ideas and solutions that deserve further attention and implementation (Luo *et al*., 2021). Together, these innovation activities are referred to as innovation crowdsourcing mechanisms (Majchrzak and Malhotra, 2020; Qin and Liang, 2019).

PROBLEM STATEMENT

Notwithstanding the role of innovation crowdsourcing mechanisms in harnessing crowd intelligence and knowledge, there is limited evidence on how the mechanisms and structure of innovation crowdsourcing communities influence firms' innovation performance (Wu and Gong, 2019). In particular, there are three main research gaps in the literature that need to be addressed:

- First, while open innovation theory focuses on the acquisition and application of external knowledge resources, it remains unclear how the effective integration of external knowledge resources with companies' internal knowledge resources leads to improved knowledge management practices. Currently, there is a dearth of research on innovation crowdsourcing that links open innovation theory to corporate knowledge management processes.
- Second, although the structure and mechanisms of innovation crowdsourcing communities are inextricably linked to firms' innovation performance, the idiosyncrasies and subtleties of innovation crowdsourcing mechanisms and their relationships to innovation performance have not been sufficiently empirically investigated.
- Finally, previous empirical studies on innovation crowdsourcing communities have usually used simulations and questionnaires as the main research methods. However, data from simulations and questionnaire surveys are largely subjective, while innovation crowdsourcing communities collect a large amount of objective data for empirical research on innovation crowdsourcing communities through social network analysis techniques.

CONTRIBUTION OF THE STUDY

To address these research gaps, this study develops a research model drawing on the perspectives of open innovation theory (Chesbrough and Bogers, 2014) and the knowledge-based view (KBV) of the firm (Grant, 1996) to investigate how the structure and mechanisms of innovation crowdsourcing influence knowledge management and innovation performance. The research model and associated hypotheses were tested using partial least squares structural equation modelling (PLS-SEM) based on a dataset from the Microsoft Power BI community of business intelligence (BI) and analytics tools (https://community.powerbi.com/). The results of this study provide empirical evidence that organisational and technical mechanisms enabling innovation crowdsourcing are positively associated with knowledge acquisition, transformation, and crowd participation size and diversity. Innovation crowdsourcing mechanisms and knowledge transformation in turn have a strong influence on innovation performance.

THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

Innovation Crowdsourcing Mechanisms

Innovation crowdsourcing is the process of externalising and outsourcing innovation activities, primarily conducted internally within an organisation, to an indeterminably broad and diverse group of collaborating stakeholders and actors (Vianna *et al*., 2020). With the widespread adoption and enabling of Web 2.0 technologies, a growing number of companies have created interactive and dynamic collaborative communities that enable their customers to engage in online crowds and participate in the co-creation process of innovations (Liu *et al*., 2018). Recent studies on user interaction in innovation crowdsourcing communities have explored crowdsourcing mechanisms and structures (Wu and Gong, 2019). Innovation crowdsourcing mechanisms are usually composed of organisational and technical mechanisms (Wu and Gong, 2019). Organisational mechanisms refer to the formal and informal means by which community managers can maintain routine operations and community activities (Bharadwaj and Menon, 2000), such as innovative official community postings, innovative sharing of community resources, and innovative community organising activities. Technical mechanisms refer to technical skills and management techniques used by the community manager to maintain the structure and cohesiveness of the network (Qin and Liang, 2019). Both organisational and technical mechanisms support and guide knowledge management activities and enable the development, governance and convergence of innovation crowdsourcing communities (Daradkeh, 2022). Accordingly, this study postulates that:

H1: Community organisational mechanisms have a positive impact on the community structure.
H2: Community technical mechanisms have a positive impact on the community structure.

Community Structure

The rationale behind the study of community structures is based on the relationships between individuals, micro-networks and macro-structures that provide the organisational support for knowledge collaboration between community members through information sharing and communication mechanisms (Muller and Peres, 2019). As a web-based paradigm, the innovation crowdsourcing community integrates users, relationships and the whole community into a social network with specific structural characteristics. Following social network theory, Daradkeh (2022) consider innovation crowdsourcing community users as network nodes and online interactions as edges to construct innovation crowdsourcing networks. The structural characteristics of the community, such as network connectivity, network density and network cohesion (Kruft *et al*., 2019), provide a powerful resource for community development and innovation management. Wang *et al*. (2021) also identified the contributions of users who occupy central positions in innovation crowdsourcing community networks. They argued that users who hold centrally placed positions also tend to produce high-quality ideas and make more contributions to the networks. An innovation community can therefore create value by fostering actions between organisations or individuals and by influencing the knowledge management capacity of organisations. Therefore, the development of extensive external relationships can not only bring a large amount of diverse information and knowledge into the organisation, but also provide more opportunities for collaboration, thereby increasing the organisation's competitiveness. Accordingly, this study postulates that:

H3: Community structure has a positive impact on enterprise knowledge acquisition.

According to the KBV of the firm, a community is considered as a social network that emphasises the pace and effectiveness of knowledge creation, sharing and transformation (Medase and Barasa, 2019). Previous studies have shown that community structure has a positive relationship with knowledge sharing and transformation processes in the community, especially with the transformation of tacit knowledge (Pawłyszyn *et al*., 2020). In knowledge transformation, tacit knowledge is transformed into explicit knowledge. The transformation of tacit knowledge takes place in the knowledge interactions between community members. The status and standing of members in the community influence the development of knowledge sharing among members, with higher status indicating greater influence and trust among members (Medase and Barasa, 2019). Osmani *et al*. (2020) compared users in the knowledge transfer process based on their position in innovation crowdsourcing community networks. Accordingly, this method provides insight into how best to identify high-value ideas. Furthermore, based on social influence theory, Daradkeh (2022) argue that members' voices and comments are shaped by their position in the networks, suggesting that users who are centrally positioned in the network generally have a higher influence and source of innovation. Therefore, this study postulates that:

H4: Community structure has a positive impact on enterprise knowledge transformation.

As relationships between community members increase, the scope of organisational relationships and linkages increases, marginal costs decrease, marginal benefits increase, and the characteristics of external sources of innovation change (Wu and Gong, 2019). The broader the relationships between community members, the greater the resource richness and the more it influences the size and activities of the innovation crowd (Pawłyszyn *et al*., 2020; Modi and Rawani, 2020). Therefore, this study postulates that:

H5: Community structure has a positive impact on crowd participation size.
H6: Community structure has a positive impact on crowd participation diversity.

Knowledge Management and Innovation Performance

According to KBV (Grant, 1996, 2015), enterprise knowledge is one of the intangible resources that are an important component for enterprises to gain competitive advantage. The knowledge gap is one of the fundamental problems of knowledge management. When companies or individuals find that their own knowledge base does not meet requirements, they try to acquire knowledge and close the knowledge gap through processes of knowledge acquisition and knowledge transformation according to the requirements of the knowledge gap. In the processes of knowledge acquisition and knowledge transformation, information is generated and a new cycle of knowledge sharing is initiated (Abdul Basit and Medase, 2019); the knowledge management process is, therefore, actually a continuous and cyclical process. Since the application of knowledge is directly reflected in the innovation capability and productivity of firms, this study focuses on knowledge acquisition and knowledge transformation to integrate the application of knowledge into the innovation performance of firms. This study suggests that the outcomes of technological innovation, such as the number of ideas adopted and defects solved, can be used to measure innovation performance (Liu *et al*., 2020a). Accordingly, this study postulates that:

H7: Knowledge acquisition has a positive impact on enterprise innovation performance.

The transformation of required knowledge drives collaboration among community members, and knowledge transformation serves as an input for knowledge application processes among employees. Tacit knowledge is more important for organisational innovation than explicit knowledge. That is, the greater the degree of tacit knowledge transformation, the stronger the organisation's innovation capacity and the higher its innovation performance. Luo *et al*. (2021) postulated that knowledge transformation and user interaction can increase the quality of ideas, stimulate new product development and improve overall customer satisfaction. Similarly, Mathrani and Edwards (2020) structured a knowledge network for innovation from user interaction and argued that collaborative innovation fostered by external users can improve firms' innovation quality from the perspective of knowledge diffusion and transformation. Knowledge transformation is an important driver of innovation behaviour, and effective knowledge transformation is key to improving organisational innovation performance (Modi and Rawani, 2020). Therefore, this study postulates that:

H8: Knowledge transformation has a positive impact on enterprise innovation performance.

Participation Size, Diversity, and Innovation Performance

The innovation crowdsourcing process usually involves an indeterminate, usually large, group of participants whose goal is to generate ideas and create solutions together using an open call mechanism (Qin and Liang, 2019). Therefore, the size and diversity of crowd participation in innovation activities are important characteristics of the innovation community. The size of crowd participation refers to the number of actors directly connected to the community innovation resource, such as the number of contributing users, responding users and the number of contribution calls. The diversity of crowd participation can be reflected in the amount of active and passionate involvement in the community innovation resource, such as the number of user posts, responses and quality of posts (Rodriguez-Ricardo *et al*., 2018). Both the size and diversity of crowd participation are likely to influence the innovation performance of enterprises (Saez-Rodriguez *et al*., 2016). Furthermore, by interacting with product users, community managers can strengthen the understanding of products and services and improve users' ability to innovate. Accordingly, the number and proportion of ratings and comments can intuitively provide information about the creativity and quality of ideas. The submission of innovation ideas was seen as a process to increase innovation knowledge and skills; this positively contributes to innovation performance and quality (Yazdanmehr *et al*., 2020). Thus, this study postulates that:

H9: Crowd participation size has a positive impact on enterprise innovation performance.
H10: Crowd participation diversity has a positive impact on enterprise innovation performance.

Crowd participation during the innovation process can help avoid innovation bottlenecks and support the acquisition of diverse knowledge resources from the community. With increasing crowd participation, companies need to transform more heterogeneous knowledge resources. Previous studies have shown that engagement and sharing of ideas among community members can improve access to relevant and diverse knowledge during the ideation process (Yu and Liu, 2020). Furthermore, the size of crowd participation determines the breadth of knowledge transformation in organisations. Therefore, the size of crowd participation, in turn, influences the knowledge transformation life cycle and thus the innovation performance of the organisation (Westerski and Kanagasabai, 2019; Yang and Han, 2021). This study postulates that:

H11: Crowd participation size has a positive impact on enterprise knowledge transformation.

The innovation crowdsourcing community is a vibrant and collaborative network that functions seamlessly and almost without boundaries. The activities of the innovation crowdsourcing community reflect the active and enthusiastic engagement of users in the community. Yang and Han (2021) report that the amount and diversity of users' social interaction, especially their commenting behaviour, number of ideas posted and number of ideas implemented are positively associated with innovation growth and performance. Furthermore, diverse user participation promotes co-creation of ideas and is positively related to the number of ideas implemented. Diversity of crowd participation helps to reduce the cost and uncertainty of collaborative innovation, and thus influences the size and scope of community participation in the innovation process (Yan *et al*., 2018). Therefore, this study postulates that:

H12: Crowd participation diversity has a positive impact on crowd participation size.

RESEARCH MODEL

Drawing on the perspectives of open innovation theory and the knowledge-based view (KBV), this study develops a research model to investigate the impact of innovation crowdsourcing structure and mechanisms on knowledge management processes and innovation performance. As shown in Figure 1, innovation crowdsourcing mechanisms influence innovation community structure. The innovation community structure influences knowledge management processes and the size and diversity of crowd participation in innovation activities. The knowledge management processes and the size and diversity of crowd participation in turn influence the innovation performance of the firm.

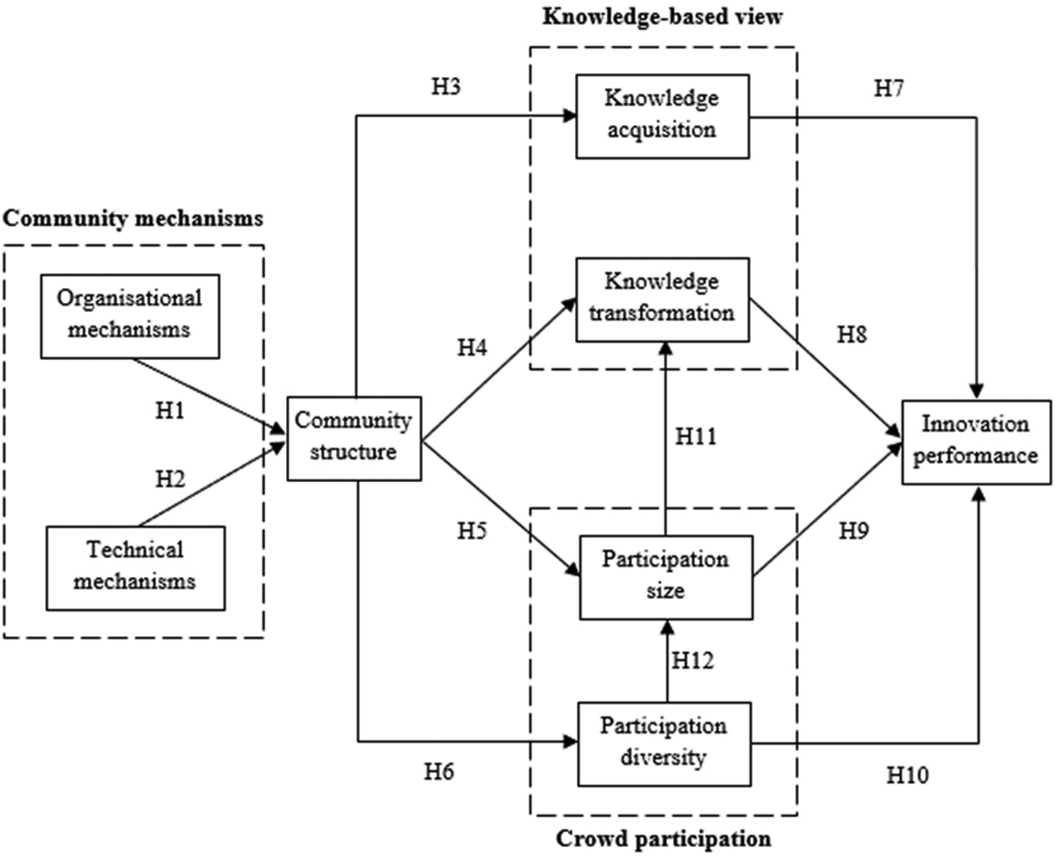

Figure 1: Research Model

Source: Constructed by authors

Method

To test the research model and hypotheses, this study used a multivariate quantitative method to analyse the data, and partial least square structural equation modelling (PLS-SEM) (Hair *et al*., 2017) to test the model's fit and identify relationships among the variables in the study.

Study Object and Settings

In this study, the Microsoft Power BI innovation crowdsourcing community was selected as the research subject (https://community.powerbi.com/). The Microsoft Power BI community is a network of experts and peers working in business intelligence, analytics, data engineering, data integration, data visualisation, data warehousing, and business performance management and reporting. It was specifically created for crowdsourcing ideas and solutions for the Microsoft Power BI product suite of self-service BI and analytics tools and technologies. Microsoft Power BI software tools enable business users to integrate multiple data sources into interactive visual reports, dashboards and analytics applications to deliver meaningful and actionable business insights that support informed decision-making and deliver more customised products and services to their customers. Key analytics components of the Microsoft Power BI product suite include Power BI Desktop, Power BI Pro, Power BI Premium, Power BI Mobile, Power BI Embedded and Power BI Report Server.

Data Collection and Pre-processing

In this study, we used the Twitter API (version 2.0.4) and the Twitter4J library (https://twitter4j.org/en/index.html) to collect data from the Microsoft Power BI community together with the corresponding idea profile characteristics for subsequent analysis. The Microsoft Power BI community received its first idea in July 2012. To stabilise the interactions around all ideas, data were crawled for all ideas in all categories posted between July 2012 and April 2021. The collected raw text data were then pre-processed and cleaned using the following methods:

1) we eliminated posts that were garbled, incorrect, or duplicated;
2) we eliminated users who posted less than five times in a year; and
3) we normalised the data before applying a PLS-SEM so that all variables contributed equally to the result.

After pre-processing, a total of 9,241 idea data for Power BI products were collected, of which 938 were completed. A total of 3,161 user records and 111,600 posts were received. These data include idea name, implementation date, publication date and idea category. The obtained dataset was aggregated by day.

Table 1 shows descriptive statistics of the variables. Based on the research hypotheses and data collected from the Microsoft Power BI community, the study variables used are as shown in Column 1 of Table 1; the descriptive statistics of the measurement indicators are shown in Columns 3-8 of Table 1. The two measurement indicators, i.e., the number of ideas completed, and number of bugs resolved, have the maximum value of 368 and 570. The average number of ideas submitted online is about 172 per month, while the average number of bugs fixed that supported the implemented ideas is about 89. The average delay date, that refers to the gap between the idea's implementation date and the publication date, is 150 days, or about 5 months.

Table 1: Measures of Model Variables

Variables	Source	Measure	N	Min	Max	Mean	SD
Organisational mechanisms	(Wu and Gong, 2019; Wang and Yu, 2020)	Official community postings	161	0	1	0.03	0.16
		Community resource sharing	19874	0	55	18.6	940.8
		Community organised activities	19874	0	955	46.5	22.7
Technical mechanisms	(Liu *et al.*, 2018; Qin and Liang, 2019)	Idea processing posts	19800	0	312	159.9	29.3
		Bug processing posts	19874	0	315	166.1	36.9
		Idea processing replies	19874	0	966	317.6	119.4
Community structure	(Martínez-Torres, 2014; Foote and Halawi, 2018)	Network centrality	63	0	25	14.6	14.4
		Network density	63	0	0.70	0.3	0.1
		Network cohesive subgroups	63	0	56	15.9	18.1
Knowledge acquisition	(Foote and Halawi, 2018; Liu *et al.*, 2020b)	New feature suggestions	9980	0	66	135.7	222.6
		Product idea feedback	19874	0	906	264.3	130.1
		Product bug feedback	19874	0	901	220.9	8.7
Knowledge transformation	(Martínez-Torres *et al.*, 2015; Martinez-Torres and Olmedilla, 2016)	Processed product ideas	19874	0	871	1.85	3.7
		Reply to product ideas	19874	0	966	31.3	16.9
		Developer communication	9984	0	966	230.4	113.9
Participation size	(Liu *et al.*, 2018; Martínez-Torres *et al.*, 2015)	Number of users	3161	0	2866	117.1	56.2
		Number of ideas	9241	0	2866	117.1	56.2
		Number of comments	111600	0	2866	821.3	437.4
		Number of views	215610	0	2916	166.2	40.8

(continued)

Table 1: Measures of Model Variables *(continued)*

Variables	Source	Measure	N	Min	Max	Mean	SD
Participation diversity	(Liu *et al*., 2020a; Martínez-Torres *et al*., 2015)	Number of user posts	111600	0	2066	242.4	117.6
		Number of user replies	19874	0	2866	281.8	134.5
		Number of high-quality ideas	938	0	2866	22.1	11.1
Innovation performance	(Dewangan and Godse, 2014; Li *et al*., 2016)	Number of bugs solved	570	0	1	0.07	0.17
		Number of ideas completed	368	0	1	0.06	0.15

Source: Constructed by authors

Data Analysis

To assess the validity and reliability of the research model, we applied partial least squares-based structural equation modelling (PLS-SEM) analysis (Hair *et al*., 2019). PLS-SEM is considered an appropriate method for this study because it allows the simultaneous estimation of multiple relationships between one or more independent variables and one or more dependent variables (Daradkeh, 2021a). In addition, because the proposed research model is intended to be used as a predictive tool for theory building, rather than theory testing, PLS-SEM is a better alternative than covariance-based SEM.

In this study, PLS analysis was performed and reported using a two-step approach, as suggested by Hair *et al*. (2019). The first step involved assessing the quality of the measurement model in terms of reliability, convergent validity, and discriminant validity (measurement model assessment). The second step involves evaluating the validity of the proposed theoretical model and assessing the strength of hypothesised causal relationships between constructs (structural model evaluation). The SmartPLS 3.0 software package was used to validate the measurement model and test the research hypotheses. Following the recommended guidelines of Hair *et al*. (2014), a non-parametric bootstrapping procedure with 5,000 replications was used to estimate the significance level of the regression coefficients and standard errors of the estimates.

RESULTS AND DISCUSSION

Reliability and Validity Analysis

Tests of reliability, convergent validity, and discriminant validity were conducted for the variables in the study (Table 2). Reliability was assessed at the variable and indicator levels. At the variable level, we examined the composite reliability (CR) and Cronbach's alpha (CA) values and found that their values were above the threshold of 0.70 (Hair *et al*., 2017). The reliability of the indicators was assessed by examining whether the loadings between variables and indicators were above the threshold of 0.70. Convergent validity was assessed by examining whether the AVE values were above the lower threshold of 0.50, with the lowest observed value being 0.67; this significantly exceeds this threshold.

Table 2: Assessment of Reliability, Convergent, and Discriminant Validity of Variables

Indicator Variable		Factor Loading*	AVE	CR	Cronbach's Coefficient
Organisational mechanisms			0.679	0.801	0.890
	Official community postings	0.788			
	Community resource sharing	0.786			
	Community organised activities	0.795			
Technical mechanism			0.671	0.829	0.860
	Idea processing posts	0.778			
	Bug processing posts	0.744			
	Idea processing replies	0.764			
Community structure			0.701	0.803	0.815
	Network centrality	0.772			
	Network density	0.706			
	Network cohesive subgroups	0.798			
Knowledge acquisition			0.720	0.806	0.836
	New feature suggestions	0.779			
	Product idea feedback	0.703			
	Product bug feedback	0.734			
Knowledge transformation			0.727	0.726	0.769
	Processed product ideas	0.764			
	Reply to product ideas	0.772			
	Developer communication	0.710			
Crowd participation size			0.718	0.744	0.793
	Number of users	0.784			
	Number of ideas	0.703			
	Number of comments	0.720			
	Number of views	0.704	0.781	0.722	0.791
Crowd participation diversity			0.759	0.739	0.771
	Number of user posts	0.782			
	Number of user replies	0.783			
	Number of high-quality ideas	0.773			
Innovation performance			0.691	0.743	0.779
	Number of bugs solved	0.741			
	Number of ideas completed	0.743			

**Note: Significant at 0.05*

Source: Constructed by authors

Discriminant validity was determined by examining the square root of the AVE values of each variable to see if it was greater than its highest correlation with another variable (Fornell-Larcker criterion) (Fornell and Larcker, 1981). As shown in Table 3, the square root of the AVE value for each variable (the diagonal elements in Table 3) was greater than the correlation between that variable and any other variable in the model; this suggests that all variables were sufficiently valid and reliable, as each measurement indicator explained more than half of the variance in its variable (Hair *et al*., 2019).

Table 3: Inter-Correlation Matrix for Variables

Variable*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Community organisational mechanisms	**0.824**							
(2) Community technical mechanisms	0.288	**0.819**						
(3) Community structure	0.571	0.427	**0.837**					
(4) Knowledge acquisition	0.561	0.487	0.307	**0.849**				
(5) Knowledge transformation	0.470	0.513	0.570	0.376	**0.853**			
(6) Crowd participation size	0.269	0.438	0.435	0.402	0.351	**0.847**		
(7) Crowd participation diversity	0.529	0.442	0.442	0.348	0.311	0.394	**0.871**	
(8) Innovation performance	0.333	0.376	0.296	0.286	0.225	0.384	0.485	**0.831**

**Note: Significant at 5%*

Source: Constructed by authors

HYPOTHESES TESTING

The results of the structural model from the PLS analysis are summarised in Figure 2, showing the explained variance of the endogenous variables (R^2) and the standardised path coefficients (β). The structural model is verified by examining the values of the coefficient of determination (R^2), predictive relevance (Stone-Geisser Q^2), and effect size of the path coefficients (f^2). The significance of the estimates (t-statistics) is determined by performing a bootstrap analysis with 5,000 replicate samples.

As shown in Figure 1, 9 of the 12 hypotheses were empirically supported. Specifically, both community organisational mechanisms and technical mechanisms were found to have an impact on community social network structure ($\beta = 0.236$, $t = 10.546$, $p < 0.01$) and ($\beta = 0.311$, $t = 10.546$, $p < 0.01$), respectively. Additionally, community structure was positively associated with business knowledge acquisition ($\beta = 0.279$, $t = 5.051$, $p < 0.01$), enterprise knowledge transformation ($\beta = 0.238$, $t = 5.051$, $p < 0.01$) and participation diversity ($\beta = 0.325$, $t = 5.051$, $p < 0.01$). In contrast, no such significant effect was found for the influence of community structure on participation size ($\beta = 0.074$, $t = 0.615$, $p < 0.05$). As also hypothesised, enterprise knowledge transformation exerts a positive and significant effect on innovation performance ($\beta = 0.221$, $t = 3.130$, $p < 0.01$), as does participation diversity (β = 0.231, t = 2.683, p < 0.01). However, no such significant effect was found for the effect of enterprise knowledge acquisition (β = 0.086, t = 0.615, p < 0.05) and participation size (β = 0.088, t = 0.615, p < 0.05) on enterprise innovation performance.

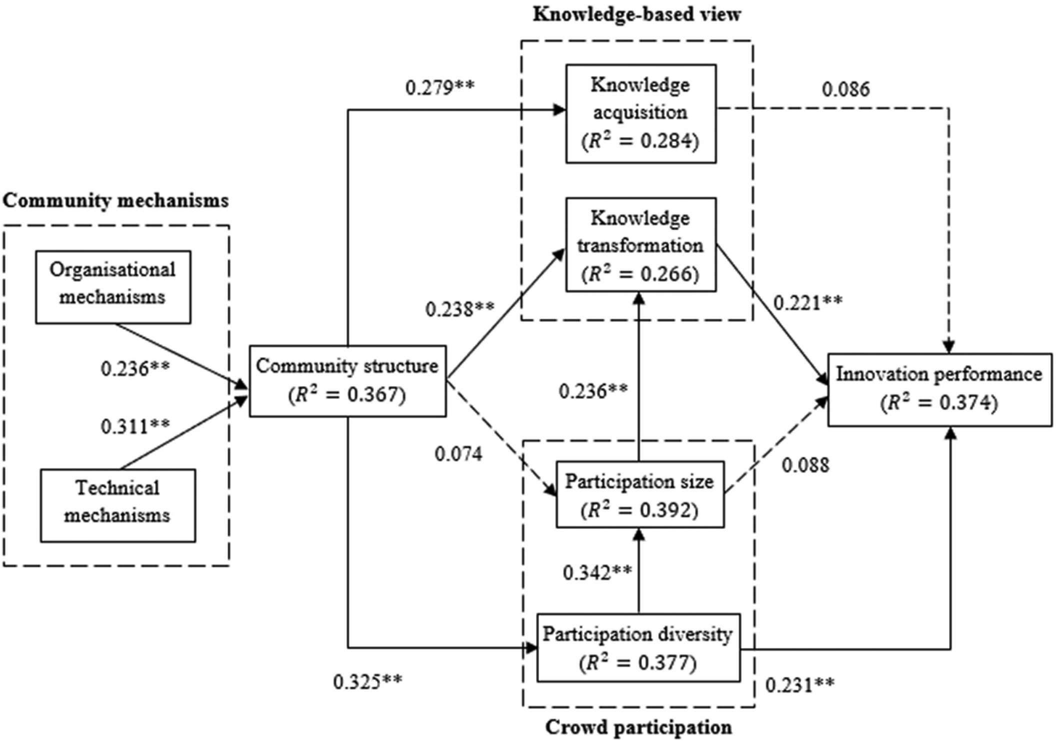

Figure 2: Path Coefficients Estimates and Explanatory Power of the Research Model
Note: ***p* < 0.01
Source: Constructed by authors

The structural model explains 36.7% of the variance for community structure (R^2 = 0.367), 28.4% for enterprise knowledge acquisition (R^2 = 0.284), 26.6% for enterprise knowledge transformation (R^2 = 0.266), 39.2% for participation size (R^2 = 0.392), 37.7% for participation diversity (R^2 = 0.377), and 37.4% for innovation performance (R^2 = 0.374). These measures of determination represent moderate to substantial predictive power (Hair *et al*., 2017). In addition to considering the R^2, the model is evaluated by considering the effect size f^2. The effect size f^2 allows us to evaluate the contribution of an exogenous construct to an endogenous latent variable R^2, and since all direct values are above the thresholds of either 0.15 or 0.35, we can conclude that they have moderate to high effect sizes.

CONCLUSIONS

This study empirically examined the role of online innovation crowdsourcing mechanisms and community structure on enterprise innovation performance. Building on open innovation theory and knowledge management processes, the findings offer insights that both organisational mechanisms and technical mechanisms are positively associated with community structure. In turn, this has a positive impact on both knowledge transformation and crowd participation diversity in the innovation process. Moreover, we found that knowledge transformation and crowd participation diversity were positively associated with innovation performance. This study offers several exploratory insights that could hopefully be useful for various stakeholders. In particular, the study might be able to provide valid information for innovation crowdsourcing managers, innovation seekers, innovators, and policy-makers. From the macro and micro perspectives, this study makes some suggestions for building and managing innovation crowdsourcing communities.

RESEARCH IMPLICATIONS

The findings of this study contribute to the current literature that has recently begun to explore the importance of online communities in the innovation crowdsourcing process by developing and empirically testing a theoretical model that conceptualises two patterns of innovation crowdsourcing mechanisms, namely organisational mechanisms and technical mechanisms. On closer examination, a number of organisational and technical mechanisms of open innovation communities can indirectly affect the innovation performance of enterprises by influencing the social network structure of open innovation communities. Therefore, it is necessary to develop and improve the organisational and technical mechanisms of open innovation communities to promote the stability and development of open innovation communities, enhance the activity of collaborative innovation sources, and therefore achieve the effect of knowledge aggregation by expanding the scope of innovation sources and improving the innovation performance of enterprises. This study contributes to the scientific understanding of the underlying success dynamics of innovation crowdsourcing communities and contributes to the innovation crowdsourcing research stream by investigating the influence of knowledge on the outcomes of innovation crowdsourcing initiatives.

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