Knowledge Contribution in Knowledge Networks: Effects of Participants' Central Positions on Contribution Quality

Sedighi, Mohammad; Hamedi, Mohsen

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Mohammadbashir Sedighi[1] and Mohsen Hamedi[2]
[1]Faculty of Technology, Policy and Management, Delft University of Technology, The Netherlands
[2]School of Mechanical Engineering, University of Tehran, Iran
M.Sedighi@tudelft.nl
mhamedi@ut.ac.ir

Abstract: Knowledge networks play a crucial role in contemporary organizations to improve participation for knowledge sharing. Examining employees' knowledge contribution play an important role for in success implementing knowledge networks. Whereas most part of studies emphasis on the quantity aspect of knowledge contributions, the success of knowledge networks also depends strongly on quality aspect of participants' voluntarily contributions. Further, employees' central positions can make a strategic position for participants for both locally and globally in the overall structure of the knowledge network. The purpose of this study is to explore the relationships between centrality positions of participants with knowledge contribution quality in knowledge networks. Five hypotheses are designed to evaluate relations of employees' centrality positions with the quality aspect of knowledge contributions using correlation analysis. The network data are collected from a knowledge network of a corporate group in the energy industry. The research results signify degree centrality; closeness centrality and betweenness centrality of participants have significant relations with the quality of shared knowledge. The research outcomes draw initial guides for organizations to evaluate the quality aspect of knowledge contributions by network analysis in knowledge networks.

1. Introduction

Organizations have recognized the growth of knowledge impacts on achieving success businesses' performance. Attention to knowledge management (KM) has grown along with the development in computers, networks, and information management systems. Successfully implementing KM and developing a knowledge-based firm is seen as an obligatory condition of success for organizations (Sedighi and Zand, 2012). Implementing KM depends on several organizational and environmental factors including measurement instruments for knowledge contributions (Sedighi et al., 2015). Moreover, the recent KM studies suggest that knowledge networks as a self-organized and open knowledge exchange platform are becoming a KM solution for an increasing number of multinational companies (Faraj et al., 2008). Knowledge networks are developed around shared goals, common interests, professional subjects, common practice, and values (Chang and Chuang, 2011). Knowledge networks are emerged among participants by asynchronous knowledge exchange technologies to overcome traditional limitations that are inherent in centralized, static knowledge sharing systems (Faraj et al., 2008; Sedighi et al., 2016).

Performance assessment as a critical part of knowledge networks and KM systems have been mentioned by some studies (Wong et al., 2014; Pugh and Prusak, 2013; Sedighi et al., 2015). While most part of prior research emphasis on the quantity aspect of knowledge contributions, the success of KM systems strongly depends on the quality aspect of participants' voluntarily contributions (Lou et al., 2013). Evaluating the quality aspect of knowledge sharing poses a major problem for organizations. Subjective nature of the quality aspect of individual contribution reduces organizations' consideration to the contribution quality. Therefore, lack of measurement mechanisms for knowledge contribution quality decreases the success rate of the knowledge network that leads participants to distrust and leave the network. Social network analysis (SNA) suggests new approach to evaluate knowledge network properties to examine participants' contributions (Helms and Reijsen, 2008). This method helps organizations to evaluate participants' knowledge contribution easer and faster. Therefore, it is crucial to clarify network indexes for evaluating participants' knowledge contribution behaviours in knowledge networks. Participants' centrality positions indexes as main structural properties represent most informative information to examine participant access to the knowledge in the overall structure of the knowledge network (Adalı et al., 2014). Furthermore, some studies have mentioned the importance of the quality aspect individual contribution (Lou et al., 2013), however few practical research explore network structure properties regarding to the quality of knowledge contribution. Therefore, this study uses network centrality indexes to explore quality aspect of knowledge contributions in knowledge networks. Thus, the outcome gets a richer insight in how network

properties relates to the knowledge contribution quality. This finding support practical managers with an initial guideline to evaluate organizational knowledge networks.

This study is organized as follows. The paper start with reviewing theoretical background related to knowledge network, knowledge contribution and participants' centrality positions within knowledge networks. Examining centrality indexes supports us to develop research hypotheses in the third section. This is followed with clarifying research methodology, research settings and data collection approach. Results, discussion and conclusion are presented in the last part of the article.

2. Background

2.1 Knowledge networks

Although several definitions and approaches have been developed in the KM literature, all approaches emphasize the role of user's participation to emerge KM. KM requires willingness on both parts of participants who have knowledge and who need knowledge (Hislop, 2013). This need is the main motivation for organization to design several knowledge sharing system for improving employees' participation and engagement (Nieves and Osorio, 2013). Knowledge networks as a self-organized and open discussion system have been developed by computer mediate technologies to promote individuals' participation around a practice or share interest (Faraj et al., 2008). These knowledge exchange platforms encourage individuals to share interests by using asynchronous communication tools. This opportunity also helps employees to overwhelm place and time limitations of face-to-face Knowledge sharing (Faraj et al., 2008).

Former studies consider knowledge network concept by investigating structure of nodes as knowledge providers and ties as knowledge relations (Hansen, 2002; Cross et al., 2002). Recent studies suggest a new direction to enable knowledge network with emerging knowledge connections within organizations. For instance, enterprise social media as a contemporary system have been emphasized by KM studies (Oostervink et al., 2016; Paul Jones et al., 2013; Leonardi et al., 2013; Menek, 2012). Knowledge networks are visualised by nodes and links. Nodes refer to the individual participants within the network, while links represent the knowledge relations between participants. Knowledge networks assign weights to knowledge connections by count of transferred knowledge objects. Further, knowledge networks are designed by a range of knowledge exchange visibility, including private knowledge exchange among individuals (e.g., instant messaging), knowledge exchange within groups (e.g., electronic networks of practice), and public knowledge exchange (e.g., enterprise discussion forums) within or between firms (Phelps et al., 2012). Knowledge networks consider knowledge sharing among participants from interpersonal perspective (Amine Chatti, 2012), which participants have autonomy to select knowledge exchange channels. Indeed, network technologies diminish the limitations of centralized knowledge sharing systems (i.e. central repositories) by subsidiary knowledge exchange through discussions rather than distributing static documents (Faraj et al., 2008). Although, several studies have been focused on knowledge networks, there have been surprisingly few studies represented to evaluate individual contributions in such environment.

2.2 Knowledge contribution in knowledge networks

Knowledge contribution represents level of participant's involvements in the KM process for sharing knowledge which can be measured by quantifying knowledge sharing behaviour (Chang and Chuang, 2011). As such, to examine knowledge sharing behaviour, we need to clarify different aspects of knowledge contribution. Therefore, defining different dimensions of knowledge sharing behaviour supports KM designers to evaluate individuals' knowledge contribution.

Employees' contribution has been defined as individuals' involvement (Chang and Chuang, 2011) or the volume of arbitrary effort of participants in a specific activity like knowledge sharing (Mergel et al., 2008). Quantity and quality have been accepted as two important sides of knowledge contribution in KM studies (Durmuşoğlu, 2013; Lou et al., 2013). Quantity of knowledge contribution represents the volume of actions in align with the KM process, while the quality of participation shows the degree of excellence participants' engagement. Most part of KM studies have considered on the quantity aspect of contribution by exploring knowledge sharing frequency (Sun et al., 2012; Kankanhalli et al., 2005), but knowledge contribution quality is left understudied with only few studies (Lu and Yang, 2011; Li et al., 2011). Low quality contribution reduces the knowledge value that can lead participants to distrust and even withdraw from the KM system. Thus, the viability and success of KM depend on users' contributions not only a large amount of participation, but also the high quality of participation. The

knowledge contribution quality is evaluated by helpfulness, accuracy and usefulness of shared knowledge, which can elucidate the inherent quality of participation of individual knowledge sharing (Sun et al., 2012).

2.3   Appraising knowledge contributions

Various methods and techniques have been developed to evaluate knowledge contributions. A main part of evaluation techniques focuses on the quantitative analysis approach. The quantitative measurement methods reduce the subjective, intangible and no-fixed standards problems which are mentioned by literature as main challenge of measuring KM performance (Wong et al., 2014). This method compensates KM systems to set measurable goals for comparing performance with other organizations.

Organizational networks analysis was initially developed to consider employees' connections in organizations (Capaldo, 2007). Besides, knowledge network analysis has been initiated through the application of SNA in the KM domain (Groth, 2003). SNA uses several methods to explore knowledge creators; knowledge connections and knowledge recipients' properties (Henneberg et al., 2009; Adkins, 2008; Cross et al., 2002). Knowledge networks analysis is not used only to indicate knowledge exchange between knowledge sources and knowledge recipients; it can be used to show emergent growth of network structure over the time. Analysing knowledge networks as a quantitative technique has been developed to measuring organizational KM performance by few studies e.g. (Nieves and Osorio, 2013; Stewart and Abidi, 2012). These studies elucidate the relationship between knowledge contribution and network properties. The knowledge network analysis focuses on the knowledge relations between participants as fundamental activities of knowledge sharing within or between organizations (Cowan and Jonard, 2009).

The knowledge network analysis clarifies different employees' categories, which represent nodes with central roles or isolated positions. This classification helps network designers to detect network ''bottlenecks''. This analysing method identifies development opportunities for knowledge flows to improve effectiveness of the knowledge exchange channels (Kazi et al., 2007). Nieves and Osorio (2013) identify several metrics by an exhaustive coverage of prior literature to clarify the link between SNA and knowledge creation and innovation. Furthermore, the combination of the macro and the microanalyses is used in the field of knowledge networks. With respect to the knowledge exchange process which is developed by individuals, micro-level behaviours in the interpersonal environment emerge knowledge network (Nieves and Osorio, 2013). Knowledge network structures emerge through individual decisions and participation through knowledge networks, which represents different levels of knowledge contribution.

2.4   Centrality and centralization

Several network metrics have been identified for understanding effects of contribution in a knowledge network. Node centrality containing degree centrality, closeness centrality, betweenness centrality and eigenvector centrality has been identified as main measures for clarifying employees' contributions. Centrality of contributors as an important index of network structure identifies valuable information about the network structure. Central employees with high centrality indexes in a knowledge network correspond participants with high quantity of knowledge links with others. This condition represents a "*well-connected*" to the network members, which can influence participants' knowledge contribution. For instance participants with high centrally indexes access to the valuable knowledge easier than other who those remain in network's periphery.

The centrality index has been studied in the social network literature. The initial studies of social network analysis focus on the "star" structure - that individuals who have many connections with their colleagues or locate in the centre of local structure. Furthermore, novel studies concern on both local and global participants' centralization. Participants are locally central if they have many relations with their neighbourhoods, while employees are globally central, when they have strategic positions in the overall structure of the knowledge network (Adalı et al., 2014). Generally, participants' centrality as an index of network structure identifies degree centrality as a local measure, while closeness centrality, betweenness centrality and eigenvector centrality have been identified as global centrality measures (Estrada, 2011).

Degree centrality (sum of out-degree centrality and in-degree centrality in directed networks) suggests those participants who have more knowledge links have more participation because they engage more on knowledge network to receive or send knowledge. The idea behind the definition of node degree as a centrality measure is that participants are more central than others in a network if their links with their neighbours are larger than

other nodes (Estrada, 2011). Centrality of knowledge networks as a type of directed network is measured by in-degree and out-degree centralizations. This classification represents the centrality aspect of participants in different levels of knowledge contribution such as read-in or post-out knowledge.

Closeness centrality indicates a situation in which participants had opportunity to reach knowledge at shorter knowledge path lengths (Rhee and Ji, 2011). Participants who have high closeness centrality are benefited from high quality of knowledge because they have been received knowledge from many people with fewer middlemen. Additionally, betweenness centrality is the extent to which a participant benefits from being on the shortest knowledge path between other participants (Henneberg et al., 2009). Participants with high betweenness centrally within a knowledge network may find it easier valuable knowledge than those on the network's periphery. This is important as this specifies how far a participant can reach other knowledge resources in the network. Networks with high average betweenness centrality show coherent knowledge network structures, which represent network participation. Furthermore, eigenvector centrality is an index to evaluate the importance of participants' neighbourhoods. Indeed, employees receive high values eigenvector centrality if they connected with other employees with high degree centrality index (Ruhnau, 2000). Likewise, a participant with high eigenvector centrality index has opportunity to gain knowledge from neighbours who have many knowledge connections with others. This measure allocates scores to all network members with respect to the neighbours' degree centrality to measure eigenvector centrality. This index can be defined for both directed and undirected networks.

3. Research hypotheses

This section develops hypotheses to examine how different employees' central positions influence the quality aspect of knowledge contribution in knowledge networks. As discussed in previous part, the success of a knowledge network as a directed network strongly depends on quality of knowledge contribution. Further, participants' read-in and participants' post-out develop knowledge network structures within organizations. Employees are located in central positions (in-degree centrality) when they acquire more knowledge from others (Helms and Reijsen, 2008). Thus, they receive more knowledge recourses, which can be used for creating valuable knowledge. On the other hand, network members invest their time, effort, energy and knowledge to share their knowledge. Knowledge network out-degree centrality represent individual post-out index. Thus, when employees focus on the number of knowledge, the quality of knowledge will be reduced due to constrains of individual resources such as time for knowledge contribution (White et al., 2011). Therefore, we proposed two hypotheses for out-degree and in-degree centralities:

> *Hypothesis 1a: in-degree (read-in) centralization of participants positively correlates with quality of knowledge contribution.*

> *Hypothesis 2: out-degree (post-out) centralization of participants negatively correlates with quality of knowledge contribution.*

The closeness centrality represents the distances of participants to all other participants as knowledge sources in the network. High closeness centrality enables participants to access to more knowledge sources over shorter paths (Adkins, 2008). Besides, high in-closeness centrality supports individuals to access more knowledge, which can improve quality of knowledge contribution. This opportunity increases the chance of receiving high value contents from others, which can improve the quality of shared knowledge. Therefore, we proposed that:

> *Hypothesis 3: in-closeness centralization of participants positively correlates with quality of knowledge contribution.*

The betweenness centrality as another measure of individuals' centrality position examines individual presence on shortest knowledge link between two other employees in the knowledge network. High betweenness centrality shows the participant contributes as a knowledge broker or a gatekeeper in the knowledge network (Bird et al., 2006). Since brokers need to acquire business and professional knowledge to transfer across organizational department (Pawlowski and Robey, 2004), they have opportunity to learn more than others. This condition enables gatekeepers to contribute with high quality of knowledge. Hence, we proposed that:

> *Hypothesis 4: betweenness centralization of participants positively correlates with quality of knowledge contribution.*

The eigenvector centrality as a subset of centrality indexes represents quality of employees' neighbours (Ruhnau, 2000). High eigenvector centrality of an employee represents node's knowledge links with knowledge sources with high centrality values in the network. Likewise, the high eigenvector centrality positively influences

quality of knowledge contribution by improving participants' positions to access high value knowledge sources within network.

> *Hypothesis 5: eigenvalue centralization of participants positively correlates with quality of knowledge contribution.*

4. Research methodology

In order to test the proposed hypotheses, all network data and qualities of shared knowledge were collected from a knowledge network of a corporate group. Descriptive statistical was employed to analyse the characteristics of network members, while the correlation analysis was used to analyse research hypotheses. Furthermore, the content analysis approach was used to measure quality of shared knowledge, while the R-package igraph (Csardi and Nepusz, 2006) as a network analysis and visualization package was used to analyse individuals' centrality positions in the knowledge network.

4.1 Research setting

Network data were used to measure participants' centrality positions in the knowledge network. The network data was collected over three month from 21st March 2014 to 21st July 2014. The knowledge network contents include a wide range of subjects around producing, installing and testing thermal power plants. Furthermore, The qualitative content analysis was employed for all knowledge objects to examine to classify manuscripts with knowledge object, question, or "others". The "other" category contains some general comments such as private message or thank you sentences. Only knowledge objects were selected for analysing the quality. The quality of shared knowledge was evaluated by items adopted from (Kulkarni et al., 2006). This model represents relevancy, accuracy, timeliness, presentation format and applicability as five elements of knowledge quality. Three independent domain experts assessed the quality attributes for each knowledge object using the five-point Likert type scales (Strongly disagree, Disagree, Neutral, Agree, Strongly agree). For instance the fir attribute was asked by this question: The shared knowledge is relevant to the company domain. Quality of shared knowledge measured by the average of elements' scores. Moreover, the participants' scores were measured by assigning the mean of knowledge objects' scores.

The network measures calculated with respect to complex network studies. Freeman et al. (1979) definitions were used to measure participants' degree, closeness and betweenness centralities, however Bonacich (1987) calculation method was employed to measure participants' eigenvector centrality positions in the knowledge network. Based on the knowledge network structure, we developed a two-modes centrality index for degree centrality and closeness centrality, one for posting knowledge (post-out) and one for reading knowledge (read-in).

4.2 Data collection

Statistics were collected from a knowledge network of a leading high-tech corporate group company in the energy industry. The company includes a parent and 36 subsidiary corporations, which operate in the area of development thermal power plants under the EPC plan as well as producing generators, turbines, power plant boilers and turbine blades. The research data were collected from one of knowledge community, which communicate about designing power plants with 107 members. The network members include engineers, production controllers, and first line managers. Table 1 represents the demographic data of active knowledge network members. The demographic data were collected from Human Resource department.

Table 1: Demographics of knowledge network members (N= 107)

Characteristics	Values	Frequency	Percentage %	Characteristics	Values	Frequency	Percentage %
Gender	Male	73	68.2	Position level	Managers	13	12.2
	Female	34	31.8		Supervisors	12	11.2
Age	18-28	8	7.5		Experts	58	54.2
	29-35	47	43.9		Technicians	24	22.4
	36-42	40	37.4	Work Experience	1-10	43	40.2
	>42	12	11.2		11-15	38	35.5
Education	Bachelor	58	54.2		16-20	14	13.1
	Master	49	45.8		>20	12	11.2

5. Results

The data collection outcome shows the knowledge network comprised of 235 knowledge contents, which read 1758 times. This contribution creates a directed knowledge network size with 1758 links and 107 nodes. Figure 1 represents the knowledge network structure, which is designed with open source Gephi software (Bastian et al., 2009). Hence, the knowledge network density is 0.152. Table 2 represents descriptive statistical data of the knowledge network of 107 network members.
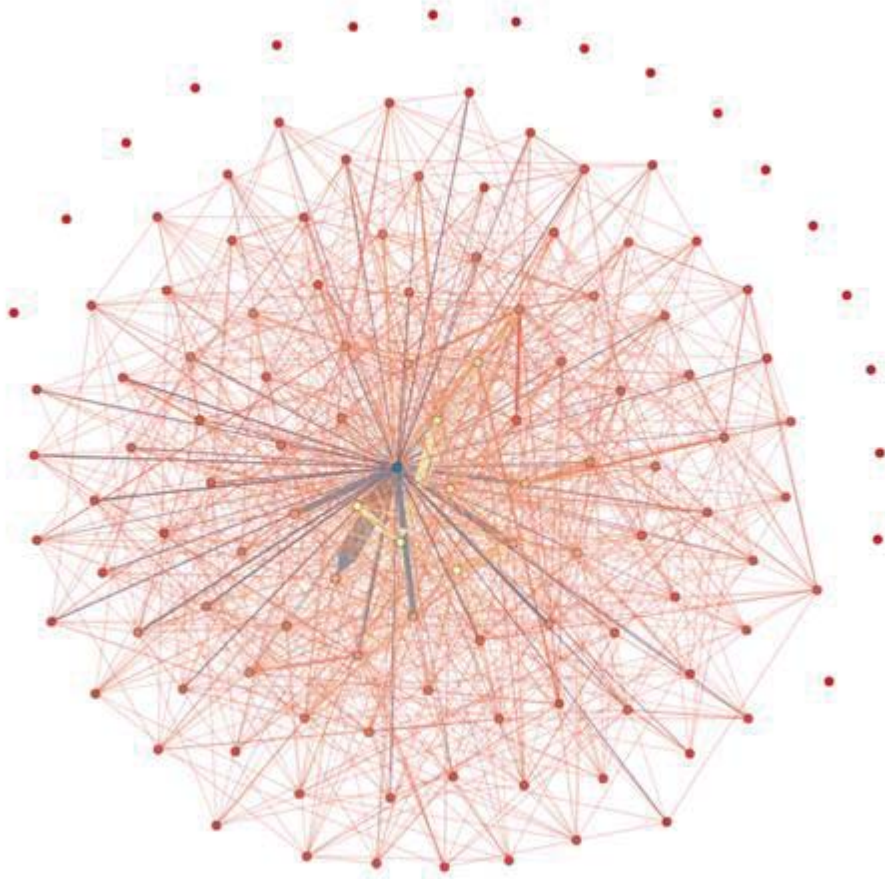

Figure 1: Knowledge network structure

Table 2: Knowledge network centrality indexes and knowledge quality

Centrality index	Mean	Variance	Std Dev	Min	Max
In-degree Centrality	16.429	601.209	24.519	0	206
Out-degree Centrality	16.429	257.889	16.058	0	138
In-closeness Centrality	0.0029	1.925E-08	0.00013	0.0025	0.0034
Betweenness Centrality	43.149	28406.75	168.543	0	1674.5
Eigenvector Centrality	0.109	0.0151	0.1229	0.014	1
Quality of shared knowledge	2.297	0.3595	0.599	1	4.8

Correlation analysis was used to test research hypotheses and clarify significant relationships between participants' centrality positions structure and quality of knowledge contribution. The results calculate with SPSS 22.0 software. The descriptive statistical table and correlation analysis result are presented in table 3.

Table 3: Correlation analysis of participants' centralities and quality of knowledge contribution

Construct	Mean	1	2	3	4	5
In-degree Centrality (1)	16.429					
Out-degree Centrality (2)	16.429	0.877**				
In-closeness Centrality (3)	0.0029	0.624**	0.474**			

Construct	Mean	1	2	3	4	5
Betweenness Centrality (4)	43.149	0.877**	0.909**	0.449**		
Eigenvector Centrality (5)	0.109	0.801**	0.647**	0.485**	0.587**	
Quality of shared knowledge (6)	2.297	0.439**	0.563**	0.311**	0.425**	0.288*

** P-value < 0.001 * P-value < 0.05

The correlation analysis results indicate that participants' in-degree centralization is significantly correlated with quality of shared knowledge (hypothesis 1). Moreover p-value is less than 0.001, which represents the positive significant correlation between employees' read-in centrality and quality of shared knowledge. Furthermore, contrary to our expectation the results show positive correlation between out-degree centrality and quality of shared knowledge (hypothesis 2). Once again, the statistical significance is less than 0.001, which represents a strong correlation between post-out contributions and quality of knowledge contribution. Likewise, in-closeness centralities of participants have a positive correlation with quality of shared knowledge (hypothesis 3). This correlation also is supported by a statistical significant p-value that is less than 0.001. Employees' betweenness centralities in knowledge network have positive significant correlation with quality of shared knowledge (hypothesis 4). This correlation is significant with a p-value (<0.001). With comparing correlation results the eigenvector centrality has a low level significant correlation with quality of shared knowledge (hypothesis 5). Moreover, the p-value is less than 0.05, which represents a significant correlation but the correlation strength is less than others. Conclusively, it can be notable that the results show strong positive correlations among network centrality indexes of employees with quality of shared knowledge in the knowledge network.

6. Discussion

The results indicate significant correlations between individual centrality indexes and quality of shared knowledge in knowledge networks. The outcomes can be interpreted that centrality indexes are logically correlated (Valente et al., 2008). For instance, out-degree centralization is positively related with betweenness centralization. This is sensible because increasing number of participants' post-out can increase the chance of remaining in the shortest knowledge paths between other employees. Moreover, the correlation analysis outcome statistically supports four hypotheses, while hypothesis 2 is rejected. Indeed the correlation between out-degree centralisation and quality of shared knowledge is statistically significant (p<0.001), but the relation is indicating in the opposed direction. A possible explanation for relationship between out-degree centrality and quality of shared knowledge is that experienced participants have propensity to share knowledge with other colleagues. Thus high contributors as skilful people like to share their knowledge with other network members. This finding is consistent with several studies e.g.(Hung et al., 2011; Lou et al., 2013), which emphasized experienced employees contribute on knowledge network because they enjoy to help others.

7. Conclusion

Knowledge networks have developed by businesses and it provided an interesting domain for academic studies. The research outcome contributes to the KM studies by exploring relations between participants' centrality positions with quality of knowledge contribution in intra-organisational knowledge networks. This research contributes to the domain of KM performance measurement by using social network analysis. The research outcome has exposed that the centrality positions have significant relation with knowledge contribution quality.

While this research uses a single dataset that is making a problem for generalizing findings, the results show participants' centrality positions significantly influence quality of shared knowledge through knowledge networks. Moreover, the results show experienced employees invest their time and effort to contribute on knowledge network regarding to both quality and quantity aspects. Finally, this study revealed new environments for future studies. Exploring relationships between other network structure's properties with contribution quality need to be focused in future research. Furthermore, future studies need to use a comprehensive data set to suggest knowledge network structure properties as a technique for evaluating knowledge contribution performance.

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