Network analysis of innovation mentor community of practice

Gunda Esra Altinisik and Mehmet Nafiz Aydin
Department of Management Information Systems, Kadir Has University-Kadir Has Campus Cibali, Istanbul, Turkey
Ziya Nazim Perdahci
Department of Informatics, Mimar Sinan Fine Arts University, Istanbul, Turkey, and
Merih Pasin
Department of Technology, Design and Innovation Management, IYTE, İzmir, Turkey

Received 27 October 2022
Revised 30 December 2022
5 February 2023
Accepted 9 March 2023

Abstract

Purpose – Positive effect of knowledge sharing (KS) on innovation has come to the fore and government-supported innovation and mentoring communities or mentor networks have become widespread. This article aims to examine the community connectedness and mentors' preferences for professional competency-based KS of such innovation community of practice networks (CoPNs).

Design/methodology/approach – The paper constructs a directed weighted CoPN model with a node-attribute-based novel fingerprint edge weights. Based on the CoPN, Social Network Analysis (SNA) metrics and measures including Giant Component (GC) were proposed and analyzed to identify mentors' connectedness preferences. The fingerprint was proposed as a novel binarized node attribute of competence. Jaccard similarity of fingerprints was proposed as edge weights to reveal correlations between competences and preferences for KS.

Findings – The work opted to conduct a survey of 28 innovation mentors to measure a CoPN. Both a name generator question and a second set of questions were employed to invite respondents to name their collaborators and indicate their professional competence. SNA metrics result in differing values for GC and the rest, which lead us to focus on GC to reveal salient metrics of connectedness. Jaccard similarity analysis results on GC demonstrate that mentors collaborate in an interdisciplinary manner.

Originality/value – Based on the CoPN, the methods proposed may be effective in predicting preferred relationships for interdisciplinary collaborations, providing the managers with an analytical decision support tool for KS in practice.

Keywords Social network analysis (SNA), Community of practice (CoP), Innovation mentors, Competences

Paper type Research paper

1. Introduction

Collaboration is one of the critical mechanisms for innovation mentors and experts to solve many complex problems (Lockhart, 2017). Without collaboration among actors, creativity and innovation may not emerge (Mellin, 2011). With this understanding, in recent years, many government-supported innovation centers have emerged in order to increase interactions in the field of innovation (Hall *et al.*, 2021). One can observe that these centers provide their members with novel services including methodologies, techniques, knowledge sharing (KS) workshops enabling an exchange of innovation practices leading to a community of practices (CoP). In essence, an innovation CoP grows and develops on the premise of establishing connectedness with their preferred peers around innovation practice. Community's strong cohesion depends on how well connected it is so that effective KS along professional competence of mentors can be obtained (Daly, 2015).

Social Network Analysis (SNA) techniques have been used by research groups in the literature, especially when examining collaborations (Meisel *et al.*, 2022). From a theory of network formation perspective (Barabási, 2012), a fully connected network, which is the

Kybernetes

0368-492X
DOI 10.1108/K-10-2022-1479

highest degree of connectedness, can be formed by any member reaching out to a random member of the community, either directly or through other members (Aydin and Perdahci, 2019). In fact, individuals having a reciprocal relationship with just one person can even split the network into more components (the largest one is called Giant Component (GC)), even if they have a collaboration between them. Consequently, reciprocal clusters within a large community may have a negligible effect on the connectedness of a community. It is important to evaluate the connectedness that may occur, as strong or weak, which affects the collaboration of communities. To examine a degree of connectedness along associated professional competence, the paper constructs a directed weighted CoP network (CoPN) model with a node-attribute-based novel fingerprint edge weights. Based on the CoPN, SNA metrics and measures including the GC are proposed and analyzed to identify mentors' connectedness preferences.

Hernández-Soto *et al.* (2021) argue that a CoP, based on the unity and competence of its members, positively affects KS. It is possible with the assortativity calculation to discover the attachments of members based on some attributes. Thus, this metric can be calculated for a single attribute category. In the literature, the importance of this has been noticed and various inferences have been made with the outputs of the communities. However, one of the main motivations of this study is whether a correlation can be observed in the similarity of competencies of the mentors. In this study, self-reports of the innovation mentors' CoP were used to find answers to the mentioned gaps. The present study opted to conduct a survey of 28 mentors to measure CoPN. Questions including a name generator were employed to invite mentors to name their collaborators and indicate their professional competence. The fingerprint is proposed as a novel binarized attribute of competence. Jaccard similarity of fingerprints was proposed as edge weights to reveal correlations between competences and preferences for KS.

2. Related work

We identify the following clusters of studies as relevant to the subject matter: CoP in an innovation context, social network perspective on Innovation Network, KS and Competencies in CoP, KS by Jaccard similarities. A summary of representative studies and their characteristics are provided in Table 1. As elaborated further in this section, this study contributes to these clusters by introducing a novel approach to innovation mentor CoP along a network perspective by which SNA metrics and Jaccard similarities for mentors' competences are employed successfully.

2.1 Communities of practices

The CoP is formed when experts with rich experiences who have competences about a theme come together with different forms including social participations, by setting a common goal to solve the problems related to this theme (Wenger *et al.*, 2002). Social participation reflects four key concepts: meaning, practice, community and identity. Wenger (1998) emphasize that these concepts are salient features of CoP and are derived from a social learning theory. As such, CoPs are critical to the emergence of innovation and can have powerful potential to generate competitive benefits (Habash, 2019). In addition, CoPs are among the leading applications in organizations with social priorities, as they provide information sharing (Al-Ghamdia and Al-Ghamdia, 2015). Scholars have examined various communities of practices in the innovation context. For instance, the impact of Innovation Centers on knowledge, innovation and entrepreneurship ecosystems in Tanzania has been analyzed with a thematic approach as a CoP (Hall *et al.*, 2021). There is also a CoP for which quantitative analyses are made, and the SNA technique is mainly used.

Relevant papers	Focus of research	Research approach	Key outcomes	Relevant open research issue
Cantner and Graf (2006)	Analysis of R&D based collaborations in Jena City, Germany, using network regression techniques through patent data	SNA used to understand the change of the network over time	Innovative mass is necessary for any technology to survive in a local system	Developing a specific SNA measurement for the collaborations
Yao *et al.* (2016)	Collaboration networks in different business disciplines with the co-citation data	SNA used to understand the network, component using centrality measurements	The average collaboration degree of the scholars of the six disciplines is relatively low	Measuring the connectedness of co-citation data
Lockhart (2017)	Interdisciplinary collaboration between type of actors	SNA used to determine the interdisciplinary collaborations along centrality measurements	An interdisciplinary collaboration is generally scientific-based, and the task group cannot maximize collaboration opportunities	Measuring the connectedness of an interdisciplinary CoP
Giusti *et al.* (2020)	Information leaks in open innovation networks including different types of actors	The degree, strong and weak components are analyzed with SNA	Makers can be an important source of information leaks	Different SNA applications innovation communities
Handzic *et al.* (2021)	Collaboration and knowledge-building mechanisms of scientific CoP	SNA was used to examine the CoP	CoP that is large-sized (successful), research focused (72% of collaborations) and growing trend over time	Research-focused collaborations have not been discovered based on competencies of the members
This Research	Analyzing connectedness and competency attributes of innovation mentor community of practice	Content-specific, component and Jaccard similarity analysis applications within the scope of SNA techniques	Interdisciplinary work among mentors	Better quality data is needed

Source(s): Author's work

Table 1. Summary of literature review

Lockhart (2017) employs SNA to examine the Mental Health-Education Integration Consortium (MHEDIC), as a CoP. MHEDIC consists of young people and their families, educators and mental health professionals working in their schools, and deals with educational protocols through interdisciplinary collaboration. Another study employing SNA analyzes the social segregation of Aboriginal and non-Aboriginal people in the region, using data from the city's volunteers and representatives from several local government and non-governmental organizations in a suburban neighborhood in the North of Australia (Ennis and West, 2012). Yet another study (Habash, 2019) examines ways to utilize outcome-based learning to enable the development of Virtual CoP (VCoP) competencies that bridge the service of innovation to enable KS and transfer.

Although SNA has been used to some extent in various innovation contexts, it has been of limited use for exploring the structure of connectedness between innovation mentors in a CoP from a theory of network (Barabási, 2012).

2.2 SNA perspective on innovation network and knowledge sharing

Organizations in highly competitive industries spend a lot of resources on innovation networks to keep up with innovations, gain connections and start new ventures (Oliver and Fortin, 2016). There are many types of innovation networks by which organizations interact with varying scopes, including regional inter-industry networks, international strategic technological alliances, and professional inter-organizational networks, supplier-user networks (DeBresson and Amesse, 1991). It has become necessary to examine these networks, which stand and exist at a critical point for both companies, industries and the economy. Also, the methods of examining these networks, which stand at a critical point, are just as essential. SNA has been used to examine innovation networks (Alberti and Pizzurno, 2015). Those SNA studies employing a network model emphasis on two basic elements of a network model, where actors (nodes) are connected to each other by ties (edges) (Ennis and West, 2010). The main purpose of SNA is to accurately measure and show structural relationships. Consequently, SNA serves to examine natural patterns formed through relationships among members of a community (Lockhart, 2017). Visuals created through nodes and edges also provide a macro structure of the network. One can observe a typical network structure as a distinguishing characteristic of innovation networks. Cantner and Graf (2006) put emphasis on the relation between network structure and along with patent data of Germany Jena city. In addition, other patent data was analyzed with SNA techniques and methods to examine the technology distribution of government-funded research (Chang, 2022). Similarly, the co-citation data of the journals were analyzed with SNA technique to measure scientific innovation and technological achievements and collaborations (Yao *et al.*, 2016). Moreover, with the three types of knowledge (technological, managerial and market knowledge) and five types of brokerage roles (coordinator, gatekeeper, liaison, representative and consultant), SNA was applied to the aerospace sector data (Alberti and Pizzurno, 2015). In another study, one of the networked universities (NU) was examined with objectives such as innovation, cost savings and strategic network solutions, which include KS among its actors and highly specialized competencies. It has been the main objective of the study to characterize NU's network cooperation and integration structure (Meisel *et al.*, 2022). However, in the reviewed studies, individuals do not appear as nodes. Instead, sectors, organizations or units are modeled as actors (Gudanowska *et al.*, 2018; Azaizah *et al.*, 2018).

While these studies are valuable for understanding innovation networks, they do not particularly address the idea of connectedness for innovation communities of practices. It should be noted that a CoP differs from a community of interest in that the members of a CoP are practitioners. In other words, CoP members take some collaborative action, and with the help of supporting services, they develop a shared repertoire of resources which can be experiences, tools, stories and ways to address recurring problems (Wenger and Trayner, 2015). Thus, a special emphasis should be put on KS along professional competences.

2.3 Knowledge sharing and competences in innovation communities of practices

Innovation activities are carried out not only in the relevant units within the company (R&D or innovation units), but also by external consultants, suppliers or intercompany (Schmitz and Strambach, 2009). Firms also collaborate to obtain research and acquire new technologies that serve their purpose, complementary skills and divide risks (Mowery *et al.*, 1998). To meet these needs of companies, many innovation centers and communities have emerged. These communities become important mechanisms for the transfer of technology and knowledge (Hooli *et al.*, 2016). Topousis *et al.* (2012) focus on collaboration-based practice and argue that it is not only a suitable platform for KS, but also plays a role in fostering collaboration and innovation. Also, CoPs indirectly generate and distribute competence in collaborative knowledge-sharing processes, i.e. building a network (Dougherty, 1995). A case study is conducted to examine the development of communities of practice, strategically aligned with the core competencies of the NASA engineering network. An "Ask An Expert" system designed specifically for this case study includes components such as collaborative interaction, compilation of discipline-specific resources and thus focuses on capabilities that increase KS (Topousis *et al.*, 2012). Giusti *et al.* (2020) examine the leaks in the open innovation community of makers through KS. Although this study focused on innovation CoP, KS is handled only for the purpose of revealing leaks. Handzic *et al.* (2021) conducted a study on KS of scientific CoP by visualizing a collaboration type with SNA.

The review shows that, while there are some studies examining innovation networks and KS, there is a need for measuring connectedness and KS with novel network metrics, which is subject to discussion in the next section.

2.4 Knowledge sharing by Jaccard similarity

The practice sharing is made possible through collaborations to fulfill knowledge needs of interacting members of a community. Filipowicz (2011) emphasizes that knowledge is formed by the ability of a possessed competence to carry out professional tasks at an appropriate level. In other words, the competencies that individuals transform into knowledge through professional and personal development and experiences (Kubat, 2014) also have an important place for practice, while they are transformed into collaborations by sharing this knowledge.

Scholars examined the CoP or networked collaborations using different techniques and applying these techniques in different contexts. However, these applications either do not include the CoP or examine KS. Therefore, examining the collaborative KS of an innovation mentor CoP with technical methods seems to be a subject that has not yet been fully addressed in the literature.

This issue can be explored as a network of CoP of mentors' collaborations, with competency attributes. Therefore, KS is examined by sharing competencies. Although there are output-based studies to examine it (Giusti *et al.*, 2020), the study of scholars who created an occupation recommendation system developed for students who do not have sufficient knowledge of what skills and abilities are needed for a particular occupation (Ochirbat *et al.*, 2017). For this purpose, Cosine, Jaccard, Intersection, Euclidean, Pearson similarity methods were used.

Similarity techniques are often used for pattern recognition problems (Cha, 2007). For instance, Collaborative Filtering (CF) is used to examine binary data with similarity techniques. Bilge *et al.* (2010) employed collaborative filtering that uses binary data and found that Jaccard and Dice measurements provided the best outputs. Bilge *et al.* (2010) argue that binary vectors also have these match principles, and that calculating linear correlation or measuring the angle between two vectors is not appropriate in the case of binary data. Therefore, Jaccard similarity seems quite suitable for measuring the similarity of mentors' competencies.

3. Methods

3.1 Data collection and modeling

The data used in this study was created from the self-reports of a group of innovation mentors who came together under a nation-wide innovation mentoring program to evaluate and establish corporate innovation systems for companies in Turkey. The work opted to conduct a survey of 28 mentors to measure CoPM. Questions including a name generator were employed to invite mentors to name their collaborators and indicate their competencies. Mentors' names are shown as randomly assigned numbers throughout the entire research to protect privacy. The content of self-reports includes the collaborated members of the community under the program and the attributes that each mentor has: these attributes are competencies of these mentors. All this information helped a visual printout of the network and a detailed analysis.

SNA methods and techniques are used to examine the connectedness and the degree of preferential attachments. The analysis is based on a survey of 28 innovation mentors who approved the anonymous sharing of results. In social network theory, a network contains nodes that may or may not be connected to each other (Graf, 2017), and the connection between nodes is expressed by edges. These connections provided by edges in an innovation mentor network represent the collaboration between mentors provided by nodes. Before moving on to the attributes of the network's nodes, it is of critical importance to examine how the network shows connectedness within itself as a first step.

Not all members of a network may always be in a single common cluster and may be subdivided. So, independent components emerge in the network. The component that contains the most interconnected members is called the GC (Aydin and Perdahci, 2019). To understand the connectedness of the network and for the analysis to yield meaningful results, the GC must be exposed. Then, the reciprocity and transitivity were calculated to understand the connectedness of GC.

After GC emerged, all analyses were based on GC and the whole network; and they were benchmarked because different components, which are disconnected from each other, create a separate network within themselves and do not show the characteristics of a complete network. After the final version of the network was created, the Jaccard similarity was applied to understand mentors' preferential collaboration with other mentors for their competencies.

3.2 Data analysis

After the data were collected, the work was continued with the visualization to understand the structure of the network. It started with creating edge and node lists, then transferred to Gephi, which is an open-source software that allows for visualization and discovery of all types of networks (Bastian *et al.*, 2009). All the components emerged with this visualization stage. Then, GC was detected, and new edge and node lists were created according to the GC. The details of the list will be explained later. After the GC was observed using Gephi and was visualized just as GC, the other steps were taken for both GC and the whole network. Also, the igraph package was used in R Statistical Language to calculate the assortativity, reciprocity and transitivity measurements. Assortativity is the measurement of whether the relationship between higher-degree nodes and other higher-degree nodes is established according to the high-degree (Newman, 2003). The formula for assortativity coefficient, which can take values between 1 (same degrees collaborate) and -1 (opposite degrees collaborate) and gives preferential collaboration output, is shared in Table 2.

In a network, reciprocity is a measure of how the members cooperate. It is found by dividing the maximum mutual connection that can occur in a network by the number of existing counterpart connections. Transitivity is the reciprocity of tripartite relations. There is also centrality measurements; and they provide the emergence of critical positions according to different factors. Degree centrality enables the identification of effective and high communication power actors (Prell, 2012). But as Prell points out, in some cases, how many people you know becomes less important than the people you know. Betweenness centrality measures the position of the current actor relative to other actors and reveals how effective the actor is in the information flow (Wasserman and Faust, 1994). Closeness centrality, on the other hand, calculates which actor can reach all actors most easily. All these measurements are used to understand this network.

Finally, different methods were used to measure the level of correlation of the similarity of competencies when the collaboration of innovation mentors is considered a network. The first

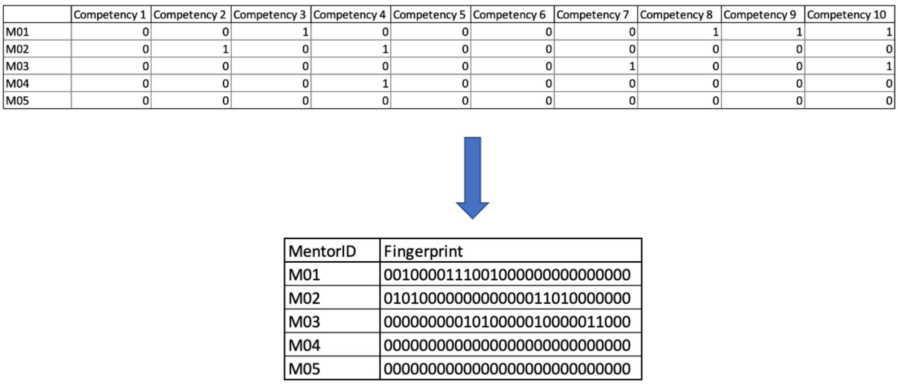
		CoPN	GC
Total Number of Nodes	N	50	33
Total Number of Edges	E	55	44
Average In-Degree	$\frac{E}{N}$	1.100	1.333
Average Out-Degree	$\frac{E}{N}$	1.100	1.333
Average Degree	$2\frac{E}{N}$	2.200	2.667
Average Shortest Path Length	$\frac{1}{N(N-1)}\sum_{i,j=1,N;i\neq j} d_{i,j}$	2.350	2.452
Average Closeness Centrality	$\frac{(N-1)}{N}\sum_{i=1,N}\left[\frac{1}{\sum_{i,j=1,N;i\neq j} d_{i,j}^{out}}\right]$	0.309	0.287
Average Betweenness Centrality	$\frac{1}{N(N-1)(N-2)}\sum_{i=1,N}\left[\sum_{i\neq j\neq t}\frac{d(t)_{i,j}}{d_{i,j}}\right]$	0.002	0.006
Assortativity	$\frac{\sum_{jk} jk(e_{jk}^{out,in}-q_{\leftarrow j}^{out}q_{\rightarrow k}^{in})}{\sigma_{\leftarrow}^{out}\sigma_{\rightarrow}^{in}}$	0.011	−0.118
Reciprocity	$\frac{E^{\leftrightarrow}}{E}$	0.072	0.091
Transitivity	$\frac{3\times Number\ of\ Triangles}{Number\ of\ Connected\ Triplets}$	0.201	0.213
Components		7	1
Giant Component	$\frac{N_{GC}}{N}$	0.660	1

Source(s): Author's work

Table 2.
SNA of CoPN

five competencies of each mentor which are within a GC were selected due to the disproportionateness of competencies. For the analysis of competencies, a fingerprint was created, consisting of the same ranking for each mentor, to see whether they have 26 competencies, and then to find fingerprint similarities. This similarity was measured with the matching competencies between two mentors; and Jaccard similarity for binary implementation was created by developing a custom R Script.

To calculate the Jaccard similarity between nodes that relate to an edge, there is a need for a fingerprint. The fingerprint of nodes is simply an array of 26 binarized numbers. As shown in Figure 1, the columns are created to correspond to competencies and the rows to correspond to MentorID. The 26 competencies created are composed of the competencies specified by the mentors in the node list. Thus, a specific competency fingerprint for each



	Competency 1	Competency 2	Competency 3	Competency 4	Competency 5	Competency 6	Competency 7	Competency 8	Competency 9	Competency 10
M01	0	0	1	0	0	0	0	1	1	1
M02	0	1	0	1	0	0	0	0	0	0
M03	0	0	0	0	0	0	1	0	0	1
M04	0	0	0	1	0	0	0	0	0	0
M05	0	0	0	0	0	0	0	0	0	0

MentorID	Fingerprint
M01	001000011100100000000000000000
M02	010100000000000000110100000000
M03	000000000101000000100000011000
M04	000000000000000000000000000000
M05	000000000000000000000000000000

Source(s): Author's work

Figure 1.

mentor was created. According to the fingerprint, it is 1 if there is a corresponding competency, and 0 if there is not.

Later, these fingerprints were created as edge attributes in R and made suitable for calculating similarity. The formula used for Jaccard similarity binary implementation is given below:

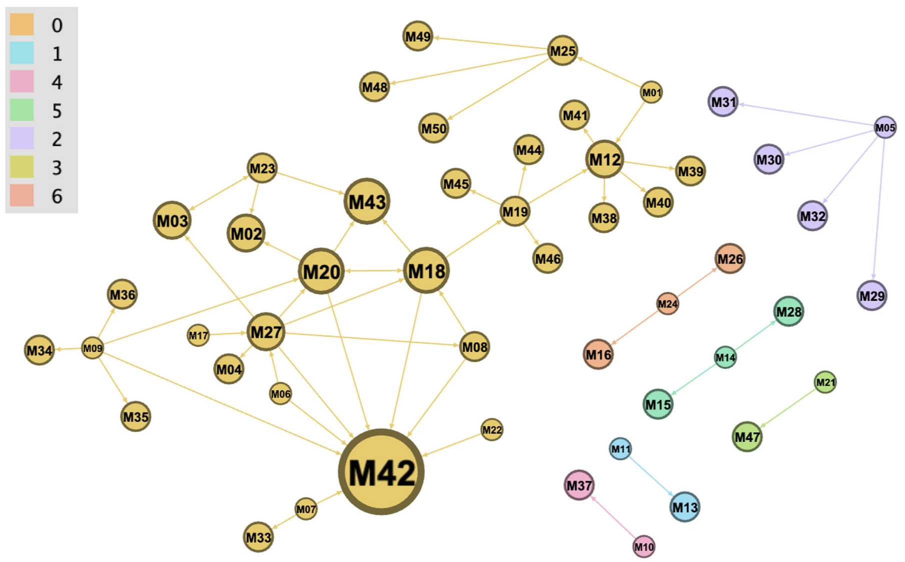
$$J(i,j) = sim(i,j) = \frac{TP}{TP + FP + FN} \tag{1}$$

The Jaccard similarity between two connected nodes is simply taking the True Positives (TP) which means the common competencies, divided by the sum of False Positive and False Negatives, one of which has the competency and the other does not, adding True Positives. So, True Negatives are not considered because the effect of both nodes not having the competency doesn't make sense in terms of similarity.

4. Results

4.1 Connectedness measured with SNA metrics

Examining the structure of the innovation mentor network is done at the macro level (i.e. the whole network) and with the component analysis for benchmarking. The whole network has seven components, one of which is visibly large. If the total nodes in the first-largest component comprise more than 50% of the entire network, and the second-largest component does not exceed this ratio, the first component in the network is considered GC (Aydin and Perdahci, 2019). As shown in Figure 2, each component is colored differently; 66% of this network is in the GC which is colored yellow and labeled as Component 0 by convention; most of the



Note(s): The colors show which component it is included in, and nodes in the same component are shown with the same color and each color represents a different Component ID that is labelled 0 through 6

Source(s): Author's work

Figure 2.
Mentor network: the size of the nodes is arranged according to their in-degree value, with the largest node having the highest in-degree value

community belongs to a group that can interact. So, GC consists of Component 0 only, hence Component 0 will be named GC from now on. Also, Table 2 shows that the number of nodes of the entire network is 50, while the number of GC nodes is 33. It is also a component that holds the majority of connections with the GC 44 edge, while the entire network has 55 edges.

The size of the nodes in Figure 2 was determined according to the in-degree of the mentors. M42, who was reported to have collaborated with eight mentors, has the highest number of in-degrees and is an essential node for this network in terms of a degree centrality measure. Average shortest path length of the whole network is 2.452, and the average degree is 2.2. Average path length of GC remains the same as the whole network while the average degree rises to 2.667 (see Table 2, where $d_{i,j}$ denotes distance). The assortativity of GC is -0.118 as shared in Table 2 (where e_{jk}, $q_{\leftarrow}$, σ refer to the degree correlation matrix, probability of finding a node with a specific degree in the direction specified by the arrow, and the corresponding standard deviation, respectively); and this shows that some high-degree mentors collaborate with low-degree mentors. For the whole network, mentors do not have any preference according to the degree as the measurement is close to zero with a value of 0.01. While the reciprocity value is 0.09, the transitivity value is 0.21; it is possible to say that triadic relations are more robust than bilateral relations. While 17 people reported that they collaborated with only one person in this network, two people reported that they collaborated with eight people; top-degree measurements can be seen in Table 3.

One can observe that the most significant differences were in the Average Betweenness Centrality and assortativity coefficient measurements. Although there was a GC of 0.66 in the innovation mentor CoP, bilateral and triadic collaborations could not make a significant difference compared to the whole network and remained at a low level of 0.091 and 0.213. In this case, it has become important to examine the assortativity measures that give different positive and negative values for the GC and the whole network.

As seen in Figure 2, the mentor with the highest connectivity is M42 and is visualized as the largest node. However, M18, with the highest betweenness centrality, which is 0.059 has a critical position; and in the absence of M18, the GC splits into two. The same can hold true for M19, which is the second highest position with a value of 0.056 in the betweenness centrality measurement. At this point, it is possible to say that nodes with high betweenness centrality values are important actors for GC formation.

	Betweenness centrality	Degree	In-degree	Out-degree
M18	0.059	7	3	4
M19	0.056	5	1	4
M12	0.036	6	2	4
M27	0.035	8	2	6
M20	0.019	7	3	4
M25	0.003	4	1	3
M3	0.003	3	2	1
M23	0.002	4	1	3
M42	0.000	8	8	0
M9	0.000	5	0	5
M43	0.000	3	3	0
M8	0.000	3	1	2
M2	0.000	2	2	0
M1	0.000	2	0	2
M6	0.000	2	0	2
M7	0.000	2	0	2
M4	0.000	1	1	0

Source(s): Author's work

Table 3. Network centrality analysis of GC

4.2 Jaccard similarity

It is worth noticing that the assortative coefficient measuring mentors' collaborative preferential attachments is negative in the GC and positive in the whole network. This assortativity coefficient is calculated with the values assigned to the nodes (Csardi and Nepusz, 2006). If a node (mentor) had only one competency, it would be possible to calculate the preferential attachments of the competency attribute in this CoPN. However, since a mentor has multiple labels under the competency heading, it would not be correct to measure the assortativity coefficient for competencies, which can calculate the correlation of a single attribute.

In this study, while 28 of the 50 mentors shared their professional competencies through self-reported data, 22 mentors from the entire network did not choose to complete this part of the questionnaire, as seen in Table 4. Forty-four innovation-based collaborations were found among 33 mentors in GC. Also, 17 of these 33 mentors shared their competencies. Since GC plays a critical role in characterizing the whole network, we examine GC *per se*.

As seen in Table 5, a total of 26 different types of competencies have been identified, 14 of which are academic and 12 are field competencies. The design-oriented competence, which was

Table 4. Shared competency summary of network

	CoPN	GC
N	50	33
E	55	44
Self-reported professional competencies	28	17

Source(s): Author's work

Table 5. Competencies of mentor network: competencies may have two categories. Those starting with "A_" indicate academic, and those starting with "F_" indicate field competence

Competency	Frequency
A_Design Oriented	9
A_Digitalization	6
F_Market Research	6
F_Technology Map	6
A_Market Research	5
F_Design Oriented	5
A_Innovation Culture	5
F_Project Management	4
F_Digitalization	4
A_Project Management	4
F_R&D Processes	4
A_Branding	3
F_Intellectual Property Rights	3
A_Lean manufacturing	3
F_Data Analysis	3
F_Change Management	2
F_Branding	1
A_Change Management	1
F_TRIZ	1
A_Organization Development	1
A_Foreign Trade	1
A_Data Analysis	1
A_Intellectual Property Rights	1
A_Supply Chain Mng	1

Source(s): Author's work

declared to be owned by 9 mentors, was the type of competence held the most, as shown in Table 4. Among the academic competencies, change management, organization development, foreign trade, data analysis, intellectual property rights and supply chain management are competencies possessed by only one member. Although there are 26 (41%) of 44 collaborations, they do not have any competencies fully common, as shared in Table 6. There is only 1(2%) collaboration with a maximum of 4 competency matches in total. At this point, Table 5 shows that mentors collaborate more with the ones that have fewer common competencies with them. However, if we consider that 27 of the participants do not share their competencies, this may change if they did. The effect of competencies on collaborations was calculated using Network Analysis. In addition, a similar ratio can be seen when Jaccard similarity is applied, as shown in Table 6. According to this table, one can conclude that mentors do more interdisciplinary collaboration. According to Jaccard similarity, one hundred percent similarity has never been seen, while 0.67 similarity accounts for only 2% of all collaborations.

The GC visualized with weighted edges according to the Jaccard similarity scores is shown in Figure 3. A thick edge represents high similarity, and that means the significant number of competencies are the same. Members of this innovation mentors' CoP collaborate more with mentors having competencies they do not possess.

5. Discussion

Nowadays, innovation networks have become an important mechanism for the development of companies, national programs and economies with their natural feature of knowledge diffusion. In recent years, with the support of the government, valuable mentorship activities have been observed in innovation centers and communities, which stand at a sensitive point for the development of economies. A significant one of these communities is the CoP of innovation mentors who do provide companies with a set of innovation management-related competencies. On the other hand, specialized in innovation management in the same community, these mentors also have other competencies which are different along with their academic and industry backgrounds. Thus, their connectedness with their preferred peers is of utmost importance to effectively sharing their valuable practice as a community. These communities of practices are like a bridge in the diffusion of innovation. This diffusion simply occurs with KS of mentors. This study emphasizes the degree of connectedness through the collaboration of mentors as a whole and examines the GC as signifying cluster of mentors separately. Furthermore, to give practical advice, the entire network and GC should be

Source	Target	Competency match	Jaccard similarity
M27	M4	4	0.667
M6	M27	3	0.429
M18	M19	3	0.429
M9	M20	2	0.250
M18	M20	2	0.250
M20	M18	2	0.250
M23	M3	2	0.250
M8	M18	1	0.111
M20	M2	1	0.111
M27	M18	1	0.111
M27	M3	1	0.111
M27	M8	1	0.111
M27	M20	1	0.111

Source(s): Author's work

Table 6. Competency collaboration measurements of network

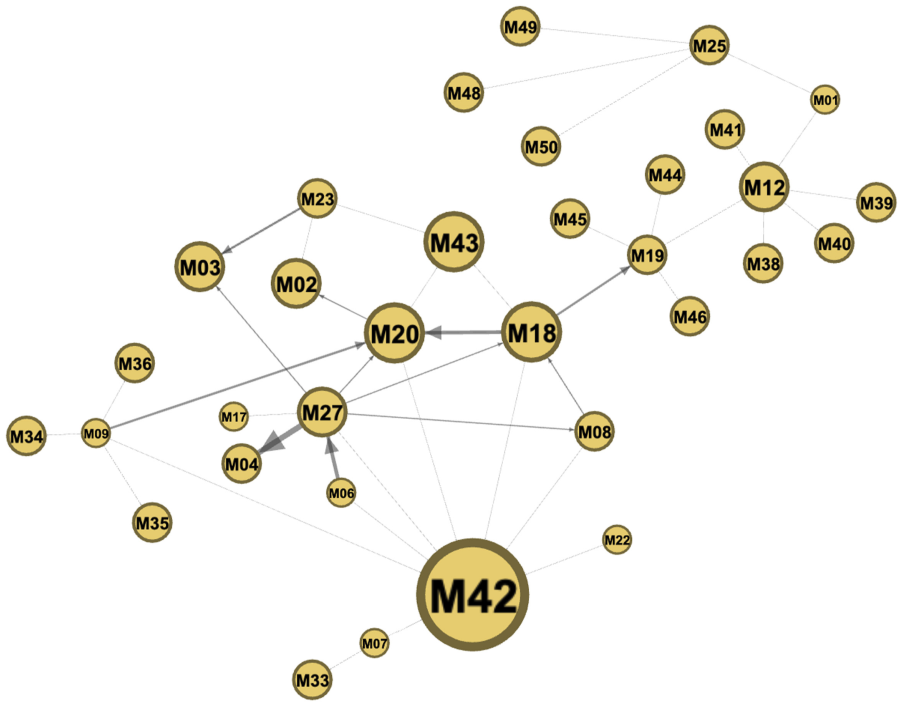


Figure 3. Competency similarity weighted mentor network: the size of the nodes is arranged according to their in-degree value, with the largest node having the highest in-degree value

Note(s): The edge thicknesses are weighted according to the Jaccard Similarity scores. The scale of thickness is between 0-0.67

Source(s): Author's work

examined separately because when looking at the GC and the Whole Network, their outputs are different, and they have different network structures.

One can see that the results in terms of degree assortativity differ significantly for the Whole Network and GC. Regarding the degree assortativity, the value of the Whole Network is positive and close to zero, while in GC, this value is negative. In other words, while preferential attachment is not identified in Whole Network, one can argue that a minority of mentors cooperating with other mentors with varying degree values exhibit conscious choices of mentors along professional competencies in GC. This innovation CoP created 66% GC and did not show full connectedness, which can be considered a sign of their conscious choices. In this study, the competency attributes of mentors were turned into a fingerprint and examined by implementing Jaccard similarity on the edge list created with SNA. According to the findings, the majority of mentors' collaborations had a low rate of Jaccard similarity. In this context, it has been understood that mentors collaborate on a more interdisciplinary level.

The fingerprint of professional competencies of mentors proposed in this work is novel but utilized a similar concept to vectorized individual attribute weights information (independently of our work) for proposing a solution to the social network group decision-making problem (Liu *et al.*, 2022, 2023). Liu *et al.* believe, and we concur, that individuals might have a multitude of attributes that are relevant to a given context, thus, scholars should pursue the goal of including appropriate mathematical representations of edge weights that could be able to incorporate many attributes into models.

Our results are promising; however, they are not without limitations. Firstly, our methods can reveal a "snapshot" of patterns that may change over time while the community evolves and mentors change (Lockhart, 2017). The innovation mentor CoP is a professional network; however, some may not prefer to report their collaborators. The fact that 28 out of 55 mentors agreed to report their collaborators limits the clarity of the analysis. It is predicted that more precise results can be obtained with more complete data. Secondly, we have access to limited information about the mentors. For instance, it is not specified whether the members have recently joined the innovation mentor CoP. Thirdly, it is another question to determine the threshold value while measuring the collaboration of mentors based on their competencies. To overcome these limitations, more data and more attributes should be reported. It is also important that more innovation CoPs are analyzed as a network using SNA techniques.

6. Conclusion

An effective innovation CoP is the key enabler for an innovation program, given the cross-disciplinary nature of the innovation process. Therefore, it is of utmost importance to analyze such CoP and underlying connectedness between participating members.

In this paper, to what extent the desired degree of connectedness is achieved on an innovation CoP is analyzed and discussed. The connectedness in question is evaluated by CoPN and Jaccard similarity in terms of professional competence preference for KS.

The results of the study confirm that the proposed CoPN can model the connectedness of an innovation CoP. Existence of a GC can signify the achievement overall connectedness in CoP. After component analysis of CoPN, it emerges that the innovation CoP contains a GC. To put it differently, the existence of GC corroborates the premise that an innovation CoP grows and develops in time to establish connectedness with their preferred peers around innovation practice. Critical information has to be embroidered on a network model to overcome the interpretability issues. To this end, the fingerprint is proposed to embroider the model after which it emerges that mentors prefer to collaborate in an interdisciplinary manner. Based on the CoPN, the methods proposed may be effective in predicting preferred relationships for interdisciplinary collaborations, providing the managers with an analytical decision support tool for KS in practice. One can leverage connectedness-driven intelligence to monitor sustainability of innovation practice of community and examine dynamics of connectedness in CoP.

References

Al-Ghamdia, H.A.K. and Al-Ghamdia, A.A.K. (2015), "The role of virtual communities of practice in knowledge management using Web 2.0, international conference on communication, management and information technology", *Procedia Computer Science*, Vol. 65, pp. 406-411, doi: 10.1016/j.procs.2015.09.102.

Alberti, F.G. and Pizzurno, E. (2015), "Knowledge exchanges in innovation networks: evidences from an Italian aerospace cluster", *Competitiveness Review*, Vol. 25 No. 3, pp. 258-287, doi: 10.1108/CR-01-2015-0004.

Aydin, M.N. and Perdahci, N.Z. (2019), "Dynamic network analysis of online interactive platform", *Information Systems Frontiers*, Vol. 21 No. 2, pp. 229-240, doi: 10.1007/s10796-017-9740-8.

Azaizah, N., Reychav, I., Raban, D.R., Simon, T. and McHaney, R. (2018), "Impact of ESN implementation on communication and knowledge-sharing in a multi-national organization", *International Journal of Information Management*, Vol. 43, pp. 284-294, doi: 10.1016/j.ijinfomgt.2018.08.010.

Bastian, M., Heymann, S. and Jacomy, M. (2009), "Gephi: an open source software for exploring and manipulating networks", in Adar, E., Hurst, M., Finin, T., Glance, N., Nicolov, N. and Tseng, B.

(Eds), *ICWSM-09 Third international AAAI conference on weblogs and social media*, AAAI Press, Menlo Park, CA, pp. 361-362, doi: 10.1609/icwsm.v3i1.13937.

Barabási, A.-L. (2012), "The network takeover", *Nature Physics*, Vol. 8, pp. 14-16, doi: 10.1038/nphys2188.

Bilge, A., Kaleli, C. and Polat, H. (2010), "On binary similarity measures for privacy-preserving top-N recommendations", in Cordeiro, J., Virvou, M. and Shishkov, B. (Eds), *ICSOFT 2010: Proceedings of the 5th International Conference on Software and Data Technologies*, University of Piraeus, Greece, Vol. 1, pp. 299-304.

Cantner, U. and Graf, H. (2006), "The network of innovators in Jena: an application of social network analysis", *Research Policy*, Vol. 35 No. 4, pp. 463-480, doi: 10.1016/j.respol.2006.01.002.

Cha, S.H. (2007), "Comprehensive survey on distance/similarity measures between probability density functions", *International Journal of Mathematical Models and Methods In Applied Sciences*, Vol. 1 No. 4, pp. 300-307.

Chang, S.H. (2022), "Technology network and development trends of government-funded patents", *International Journal of Innovation Science*, Early Access: May 2022, doi: 10.1108/IJIS-12-2021-0234.

Csardi, G. and Nepusz, T. (2006), "The igraph software package for complex network research", *InterJournal, Complex Systems*, Vol. 1695 No. 5, pp. 1-9.

Daly, A. (2015), "Refocusing the lens: educational research in an era of relationships", *Journal of Educational Administration*, Vol. 53 No. 1, pp. 140-147, doi: 10.1108/JEA-11-2014-0135.

DeBresson, C. and Amesse, F. (1991), "Networks of innovators: A review and introduction to the issue", *Research Policy*, Vol. 20 No. 5, pp. 363-379, doi: 10.1016/0048-7333(91)90063-V.

Dougherty, D. (1995), "Managing your core incompetencies for corporate venturing", *Entrepreneurship Theory and Practice*, Vol. 19 No. 3, pp. 113-135, doi: 10.1177/104225879501900308.

Ennis, G. and West, D. (2010), "Exploring the potential of social network analysis in asset-based community development practice and research", *Australian Social Work*, Vol. 63 No. 4, pp. 404-417, doi: 10.1080/0312407X.2010.508167.

Ennis, G. and West, D. (2012), "Using social network analysis in community development practice and research: a case study", *Community Development Journal*, Vol. 48 No. 1, pp. 40-57, doi: 10.1093/cdj/bss013.

Filipowicz, G. (2011), *Uniwersalny Model Kompetencyjny. Podręcznik Użytkownika [A Universal Competence Model. User's Guide]*, Fundacja Obserwatorium Zarządzania, Warszawa.

Giusti, J.D., Alberti, F.G. and Belfanti, F. (2020), "Makers and clusters. Knowledge leaks in open innovation networks", *Journal of Innovation and Knowledge*, Vol. 5 No. 1, pp. 20-28, doi: 10.1016/j.jik.2018.04.001.

Graf, H. (2017), "Regional innovator networks: a review and an application with R", *Jena Economic Research Papers*, available at: http://hdl.handle.net/10419/174376 (accessed 24 March 2023) (in preparation).

Gudanowska, A.E., Alonso, J.P. and Törmänen, A. (2018), "What competencies are needed in the production industry? The case of the Podlaskie Region", *Engineering Management in Production and Services*, Vol. 10 No. 1, pp. 65-74, doi: 10.1515/emj-2018-0006.

Habash, R. (2019), "g9toengineering: a virtual community of practice in knowledge creation", in Ashmawy, A.K. and Schreiter, S. (Eds), *EDUCON Global Engineering Education Conference*, American University in Dubai (AUD), Dubai, pp. 1504-1511, doi: 10.1109/EDUCON.2019.8725236.

Hall, A., Mwantimwa, K.M., Ndege, N.R. and Atela, J.I. (2021), "Scaling innovation hubs: impact on knowledge, innovation and entrepreneurial ecosystems in Tanzania", *Journal of Innovation Management*, Vol. 9 No. 2, pp. 39-63, doi: 10.24840/2183-0606_009.002_0005.

Handzic, M., Bratianu, C. and Bolisani, E. (2021), "Scientific associations as communities of practice for fostering collaborative knowledge building: case study of IAKM", *Electronic Journal of Knowledge Management*, Vol. 19 No. 2, pp. 91-104, doi: 10.34190/ejkm.19.2.2369.

Hernández-Soto, R., Gutiérrez-Ortega, M. and Rubia-Avi, B. (2021), "Key factors in knowledge sharing behavior in virtual communities of practice: a systematic review", *Education in the Knowledge Society*, Vol. 22, pp. 2-16, doi: 10.14201/eks.22715.

Hooli, L.J., Jauhiainen, J. and Lahde, K. (2016), "Living labs and knowledge creation in developing countries: living labs as tool for socio-economic resilience in Tanzania", *African Journal of Science*, Vol. 3 No. 1, pp. 61-70, doi: 10.1080/20421338.2015.1132534.

Kubat, M. (2014), "Kompetencje zawodowe [Professional competences]", available at: https://wuplodz.praca.gov.pl/documents/58203/842291/Kompetencje%20zawodowe.pdf (accessed 24 September 2021).

Liu, Y., Li, Y., Zhang, Z., Xu, Y. and Dong, Y. (2022), "Classification-based strategic weight manipulation in multiple attribute decision making", *Expert Systems with Applications*, Vol. 197, 116781, pp. 1-13, doi: 10.1016/j.eswa.2022.116781.

Liu, Y., Liang, H., Dong, Y. and Cao, Y. (2023), "Multi-attribute strategic weight manipulation with minimum adjustment trust relationship in social network group decision making", *Engineering Applications of Artificial Intelligence*, Vol. 118, pp. 1-15, 105672, doi: 10.1016/j.engappai.2022.105672.

Lockhart, N.C. (2017), "Social network analysis as an analytic tool for task group research: a case study of an interdisciplinary community of practice", *The Journal for Specialists in Group Work*, Vol. 42 No. 2, pp. 152-175, doi: 10.1080/01933922.2017.1301610.

Meisel, J.D., Montes, F., Ramirez, A.M., Lemoine, P., Valdivia, J.A. and Zarama, R. (2022), "Network analysis of collaboration in networked universities", *Kybernetes*, Vol. 51 No. 4, pp. 1341-1364, doi: 10.1108/K-10-2020-0648.

Mellin, E.A. (2011), "Responding to the crisis in children's mental health: potential roles for the counseling profession", *Journal of Counseling and Development*, Vol. 87 No. 4, pp. 501-506, doi: 10.1002/j.1556-6678.2009.tb00136.x.

Mowery, D.C., Oxley, J.E. and Silverman, B.S. (1998), "Technological overlap and interfirm cooperation: implications for the resource-based view of the firm", *Research Policy*, Vol. 27 No. 5, pp. 507-523, doi: 10.1016/S0048-7333(98)00066-3.

Newman, M.E.J. (2003), "Mixing patterns in networks", *Physical Review E*, Vol. 67 No. 3, 026126, doi: 10.1103/PhysRevE.67.026126.

Ochirbat, A., Shih, T.K., Chootong, C., Sommool, W., Gunarathne, W.K.T.M., Hai-Hui, W. and Zhao-Heng, M. (2017), "Hybrid occupation recommendation for adolescents on interest, profile, and behavior", *Telematics and Informatics*, Vol. 35 No. 3, pp. 534-550, doi: 10.1016/j.tele.2017.02.002.

Oliver, D. and Fortin, I. (2016), "To imitate or differentiate: cross-level identity work in an innovation network", *Scandinavian Journal of Management*, Vol. 32 No. 4, pp. 197-208, doi: 10.1016/j.scaman.2016.09.001.

Prell, C. (2012), *Social Network Analysis: History, Theory and Methodology*, 1st ed., SAGE, Los Angeles, CA.

Schmitz, H. and Strambach, S. (2009), "The organisational decomposition of innovation and global distribution of innovative activities: insights and research agenda", *International Journal of Technological Learning, Innovation and Development*, Vol. 4 No. 2, pp. 231-249.

Topousis, D.E., Dennehy, C.J. and Lebsock, K.L. (2012), "Nasa's experiences enabling the capture and sharing of technical expertise through communities of practice", *Acta Astronautica*, Vol. 81 No. 2, pp. 499-511, doi: 10.1016/j.actaastro.2012.08.008.

Wasserman, S. and Faust, K. (1994), *Social Network Analysis: Methods and Applications*, Cambridge University Press, New York, NY.

Wenger, E. (1998), *Communities of Practice: Learning, Meaning and Identity*, Cambridge University Press, Cambridge.

Wenger, E. and Trayner, B. (2015), "Introduction to communities of practice : a brief overview of the concept and its uses", available at: https://www.wenger-trayner.com/introduction-to-communities-of-practice/ (accessed 20 September 2021).

Wenger, E., McDermott, R. and Snyder, W.M. (2002), *Cultivating Communities of Practice: A Guide to Managing Knowledge*, Harvard Business School Press, Boston, MA.

Yao, X., Qi, W., Tian, H. and Wang, L. (2016), "Analysis of collaboration networks in business disciplines", *Serials Review*, Vol. 42 No. 2, pp. 98-107, doi: 10.1080/00987913.2016.1166878.

Corresponding author
Gunda Esra Altinisik can be contacted at: esragunda@gmail.com