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SOCIAL NETWORK ANALYSIS OF INNOVATION MENTOR COMMUNITY OF PRACTICE

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SOCIAL NETWORK ANALYSIS OF INNOVATION MENTOR COMMUNITY OF PRACTICE

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APPROVAL

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In addition, I acknowledge that any claim of irregularity that may arise in relation to this work will result in a disciplinary action in accordance with the university legislation.

Gunda Esra Altınışık

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Date (27/12/2022)

To My Dearest Love and Family...

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SOCIAL NETWORK ANALYSIS OF INNOVATION MENTOR COMMUNITY OF PRACTICE

ABSTRACT

Innovation is directly related to the development of economies, and with the awareness of its criticality, various nation-wide support programs and innovation communities have emerged in recent years. These communities are established along their own specific structures and dynamics that can be examined by their level of connectedness and its underlying members' attributes. In this research, a government-sponsored innovation mentors' community of practice (CoP) has been examined. Thus, the members are advised to bring their knowledge to adopt the framework to specific cases and share their experiences with their peers. A CoP stands on the basic premise that the practice (know-how) is shared among members and stimulates connectedness along their competencies. In this context, the first question is: how to measure the connectedness of the community and whether the CoP under investigation achieves the desired level of connectedness? The second is: what specific mentors' attributes (competencies) characterize the preferred choices of connectedness? More particularly, how knowledge-sharing preferences are associated by the mentors' attributes of this CoP? We employed Social Network Analysis techniques and Jaccard Similarity to answer them. The findings reveal that the CoP of innovation mentors is highly connected for a giant component, but low at the network level. Degree, title and institution as the members' attributes may not play a significant role in the connectedness of this community. Even though mentors meet on a denominator in basic competencies in their cooperation, the findings show that they cooperate interdisciplinary. We argue that the dissimilar competencies of the connected mentors can be considered as a signature of the very idea of connectedness. Further research is needed to validate this claim with richer data, preferably with a temporal aspect.

Keywords: Innovation Mentors, Social Network Analysis (SNA), Community of Practice (CoP), Knowledge-Sharing

İNOVASYON MENTÖRLERİ UYGULAMA TOPLULUĞUNUN SOSYAL AĞ ANALİZİ

ÖZET

İnovasyon, ekonomilerin gelişimi ile doğrudan ilgili olup, öneminin farkındalığı ile son yıllarda ülke çapında çeşitli destek programları ve inovasyon toplulukları ortaya çıkmıştır. Bu topluluklar, bağlılık düzeyleri ve üyelerin nitelikleri ile incelenebilecek kendi özel yapıları ve dinamikleri çerçevesinde oluşur.Bu araştırmada, devlet destekli bir inovasyon mentör uygulama topluluğu (Community of Practice - CoP) incelenmiştir. Bu nedenle, üyelere, çerçeveyi belirli durumlara uyarlamak için inovasyon uzmanlıklarını kullanmayı ve deneyimlerini akranlarıyla paylaşmaları tavsiye edilir. Bir uygulama topluluğu, üyeler arasında paylaşılan bilgi-tecrübenin değeri (know-how) için daha yüksek seviyede bağlantı kurmayı teşvik etme temel fikri üzerinde kuruludur. Bu bağlamda ilk soru, bir CoP'nin ilk temel kavramı olan topluluğun bağlantılılığının nasıl ölçüleceği ve incelenen CoP'un istenen bağlantılılık düzeyine ulaşıp ulaşmadığıdır. İkinci soru şudur: Mentörlerin hangi özel öz nitelikleri, tercih edilen bağlılık seçeneklerini ifade eder? Daha özel olarak, bilgi paylaşım tercihleri, yani uygulama konsepti, bu CoP'nin mentörlerin nitelikleri (yetkinlikleri) tarafından nasıl şekillendirilir? Bunları yanıtlamak için Sosyal Ağ Analizi tekniklerini ve Jaccard Benzerliğini kullanılmıştır. Bulgular, inovasyon danışmanlarının uygulama topluluğunun dev bir bileşen için yüksek oranda bağlantılı olduğunu, ancak ağ düzeyinde düşük olduğunu ortaya koyuyor. Derece, unvan ve kurum bu topluluğun bağlantılılığında önemli bir rol oynamadığı görülmüştür. Mentörler iş birliklerinde temel yetkinliklerde bir paydada buluşsalar da bulgular disiplinler arası iş birliği yaptıklarını göstermektedir. Bağlantılı mentörlerin yetkinlik farklılığının, bağlantılılık fikrinin bir imzası olarak değerlendirilebileceğini savunuyoruz. Bu iddiayı doğrulamak için daha fazla araştırmaya ihtiyaç olduğu ve bu amaçla daha zengin, tercihen zamansal bir yönü olan veriler kullanılması önerilmektedir.

Anahtar Sözcükler: İnovasyon Mentörleri, Sosyal Ağ Analizi (SAA), Uygulama Topluluğu, Bilgi Paylaşımı

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LIST OF SYMBOLS

δij	Kronecker delta

LIST OF ACRONMYMS AND ABBREVIATIONS

CF Collaborative Filtering

CoP Community of Practice

SNA Social Network Analysis

VCoP Virtual Community of Practice

1. INTRODUCTION

Today, innovation has an important place in the growth of countries. Although innovation is critical, innovation capability may not always be at a reachable level. For example, as part of its 2020 SME strategy, the European Commission selected mentors from leading companies and received support from them for the innovation and digital transformation of SMEs (EC 2022). For these innovation mentors and experts, collaboration is one of the critical mechanisms for to solve many complex problems (Lockhart 2017, 152). Without collaboration among actors, creativity and innovation may not emerge (Mellin 2011, 504-505; Lockhart 2017, 153). For instance, between 2012 and 2018, Knowledge and Innovation Communities created over 900 innovative products on topics such as health, climate change, energy, and digitalization (EIT 2019). With this understanding, many innovation centers have emerged in recent years in order to increase interactions in the field of innovation (Mwantimwa *et al.* 2021, 40). One can observe that these centers actually consist of communities that come together with a common innovation idea, and it would be appropriate to call each of these centers a community of practices (CoP). Thus, an innovation community of practice grows and develops on two basic concepts. The first is that the actors can form a strong association around the concept of innovation and creates a community. The second concept is to create relationships or connectedness between community members through knowledge sharing. A community's strong cohesion depends on how connected it is. However, even if these communities convene under a unifying idea; which are community of practices, may not necessarily procure that the community has a desirable degree of connectedness to achieve its goals and members fully use their capacity (Daly 2015). Collaborations with knowledge sharing constitute the practice stage of the community. Thus, examining to what extent people demonstrate connectedness and how they share knowledge in an innovation mentor community of practice is essential for the effectiveness of the community. At this point, it is valuable to be able to identify a method that can be used to measure existing questions. One of the methods that can be used for this measurement is Social Network Analysis (SNA).

Social Network Analysis (SNA) techniques have been used in the literature, especially when examining collaborations (Meisel *et al.* 2021, 1343). The fact that it is a method that can show actors and their collaborations makes it suitable for examining collaborations, and the formation of a visual of the community makes it easier to view the community from a macro structure point of view. From a theory of network formation perspective (Barabási 2012, 15), a fully interconnected community, which is the 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, pp.230). In fact, individuals having a reciprocal relationship with just one person can even split the network into more components even if they have a collaboration between them. In other words, unless there are many reciprocal collaborations that combine these binaries with other binaries, there will be no connectedness within the community even if there is a lot of reciprocal collaboration. Consequently, reciprocal clusters within a large community may have little effect on the connectedness of a community. It is important to evaluate the connectedness that may occur, as strong or weak, which is affecting the collaboration of communities in terms of many innovation communities that have gained value recently.

Many different attributes affect the community while it is evolved over time as part of the development process (Datta 2018). The connectedness of an innovation mentor's collaboration network can be achieved by maximizing collaborations. Therefore, the features preferred in collaborations can also affect connectedness. For instance, if members of a community attach importance to the popularity of a member when collaborating, popularity becomes the priority, and collaborations may shape around this attribute. In this regard, when attributes are an essential criterion for collaboration causes clustering and disconnected structure in a community, so the community may show low connectedness. Thus, there may be some attributes that affect the connectedness of a community. In this regard, measuring the preferential attachment of attributes for collaborations becomes a critical finding for the connectedness of the network. This measurement can give a clue about the preferential attachment of attributes in collaborations and whether an attribute is more prominent than the community's connectedness per se. In this study, self-reports of the innovation mentors' community of practice were used to find answers to the following key questions: to what extent does an innovation community of practice show connectedness? And how do the preferential attachments of this community affect its connectedness?

Scholars argue that a CoP based on the unity and competence of its members positively affects knowledge sharing (Hernández-Soto, Gutiérrez-Ortega and Avi 2020, 2-7). In other words, for a CoP, knowledge sharing is just as important as connectedness, which takes place within the scope of competence-based collaborations of the members and supports the formation of the practice component of the CoP. However, due to the different aspects of these components that make up the community, it is not possible to measure with the same measurement method. Because while connectedness can be viewed from the perspective of the whole community, knowledge sharing takes place on the basis of the competencies that are the individual attributes of the members. It is possible with the assortativity calculation to discover the preferential attachments of members in a community based on node attributes. However, the assortativity value is a metric that 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 knowledge types that are shared by connected actors of the communities. Thus, one of the main motivations of this study is to seek an answer for the question of whether a correlation can be observed in the similarity of competencies of the mentors. This requires a new approach to the literature as to the collaboration of innovation mentors is considered as a network and competencies are inputs in the context of practice element of the CoP.

1.1 Motivation and Challenges

Innovation communities are important to burgeoning economies. Although some innovation communities have been examined before, it has not been adequately addressing the very idea of connectedness along members' competencies. The main ambition of this research is not only to analyze this community qualitatively but also to be able to measure the connectedness and the underlying competencies at the macro and meso levels by employing SNA techniques.

Even though the community of practices has been examined with SNA, they have not been examined within the elements that make up the CoP, and some of the findings were just based on the types that are considered as actors that did not contain measurements of the collaborations. In this sense, it was necessary to be propose a network model for a CoP and enriching the model with members’ competencies as node attributes.

1.2 Summary of Contributions

This thesis presents the following research contributions;

- A new approach to examining CoP for innovation mentors
- Proposing a network model for innovation mentors community of practice
- Correlation analysis of innovation mentors' attributes and collaborations
- Analysis of innovation mentors' knowledge sharing based on competencies in terms of their collaborations.

1.3 Structure of the Thesis

First of all, in the second chapter of this study, the research background of the three basic concepts of the study; innovation, community of practice, and SNA are explained to present the scope of this research. Chapter 3 introduces a network model and the way meta-data is incorporated. Chapter 4 includes the findings and discussion in light of the SNA metrics applied. Finally, in conclusion part summarized the the whole study. We provide implications of the findings from theory and practitioner perspectives.

2. CHAPTER/RESEARCH BACKGROUND

2.1 Innovation Conceptual Framework

2.1.1 Definition of innovation

Innovation is defined as novelty brought into reality with values along the change associated with the social, economic, cultural, and administrative environment. That is, it is innovations that turn needs into benefits by using new ideas and implementing existing or new knowledge in many different ways. In other words, it is the ideation of new products, production processes, services, and organizations by improving the existing subjects or objects under examination.

With a simple definition, innovation is the stage where a different idea is brought from invention to implementation. Consequently, innovation is the process that covers the information and uses of different and useful products to be released and put on the market. This stage generally includes ideation, research, development and production, use and after-use stages. Therefore, innovation causes many processes that affect each other. In this regard, firstly, Joseph Schumpeter described that innovation-based markets are the driving force in development compared to pure price-based competition alone (Betz 2011, 33).

The concept of innovation, which has been used since the 20th century, is the main purpose for developed and developing countries and is in harmony with time and, therefore, social and technological changes. One of the most important reasons for the loss of power of empires and states established throughout the ages is due to the problems of not being able to adapt to these changing parameters or being late (Baregheh, Rowley and Sambrook 2009, 1324).

2.1.2 Importance of innovation

One of the driving forces that enable the development of the economy is innovation, which enables works, methods, time, the market, and people to constantly innovate. According to the Global Innovation Index, there is a positive relationship between innovation and a country's development (WIPO 2022). In this context, companies that have new, different, interesting, durable, and useful products with better features than those produced by competitors gain financial power, and companies that cannot develop themselves in this field are failing.

Scholars and practitioners emphasize the necessity and importance of innovation to improve the sustainability of the competitive environment. In the Global Competitiveness Report, it is stated that innovation has had an impact on global competitiveness with a score of 42 out of 100 (WEF 2019). Thus, one of the current issues of the science and technology world in recent years is not why innovation is needed but how to achieve innovation. The reason for this is to ensure the development of the business by working on new or improved products, time, techniques or procedures by showing companies an advantage in competition. In this regard, innovation is currently one of the important issues of countries, economies, companies, and science. In other words, innovation ensures that to achieve the targets for economic growth and development of states, an increase of the quality-of-life standards, and the competitive advantage among businesses develops depending on innovation (Nutu and Vlase 2015, 254).

The main reason of the increasing attention on innovation nowadays is the globalization process. While only a few products and very few competitive businesses existed in the sector in the past years, as a result of globalization, the sectors have expanded and all profit-oriented businesses have found themselves in an intense competitive environment. In this environment where the number and quality of rival businesses are increasing, the selection range of consumers has expanded. Therefore, businesses have to make a difference compared to their competitors in the products and services they offer in order to be the choice of consumers. However, another effect of globalization has been that rival firms can imitate the new ideas created very quickly. Where these conditions prevail, businesses that can innovate may be more successful than others.

Innovation emerges as the most important competitive strategy applied by companies to enter new markets, increase their current market share and achieve sustainability in the market. Today, price reductions alone are not sufficient as a means of competition.

Another grand effect of innovation for businesses is that it increases customer loyalty and ensures customer satisfaction. Innovation is an indispensable element for both today's national economies and organizations. Innovation has become an important requirement for growth for local and national economies, for the welfare and social development of society, and for growth for businesses and large economies.

Most new enterprises are born at the end of the innovation process. Businesses need constant innovation in order to maintain their competitive power. In order to maintain competitiveness, economic growth, and employment opportunities, countries need to turn their new ideas into technical and commercial success (Maier 1998, 285).

Increasing competitiveness in a country results in an increase in the standard of living in that country; The increase in competitive power is directly proportional to the increase in productivity. By transforming a country's equity into a product or service, the gaining of economic value from these products and services, on the other hand, is achieved through innovation. In this context, it appears that innovation is not only an economic subject but a social system. In the studies conducted by the researchers, the development of innovation and the increase in performance play a major role in the development of trade between countries and the long-term development of this development.

2.1.3 The importance of innovation for countries' economy

New technologies, new inventions, while affecting human life, have also caused the social and economic balance in the world to change. One of the main reasons for the emergence of these changes is globalization, and through this, the world has become a single market.

In order to get rid of this sameness as a result of globalization, companies have resorted to innovation, one of the most effective ways to increase competitiveness. Innovation not only affects the income and profit rates of enterprises but also affects the economies of the country as a development tool. In the study of Michael Porter, which investigated the relationship between the innovation capability of countries and the gross domestic product, it was revealed that there is a directly proportional graph between the innovation ability of countries and their welfare levels (Porter and Stern 1999, Chap. 2). Another importance of innovation for the country's economy is the increase in job opportunities. Because applying new ideas and adapting them to new areas requires a workforce that has expertise with different competencies. At this point, innovation plays a critical role in realizing economic growth and raising the standard of living. Its contribution to economic growth with technological developments and innovations is enormous.

Innovation, which has such a critical impact on the economies of states, therefore, plays an important role in the policies of states. Much of the United States' economic development depends on technological innovation, and one of the most striking factors known is the existence of Silicon Valley. Recognizing this added value, many countries have prioritized technological innovation in their support programs because funding resolves investment issues (Chang 2022).

2.1.4 The importance of innovation for business and its relation with policies

The competitive advantage of an enterprise over its competitors working on the same business can occur with the differences it makes. An enterprise can make a difference if it acquires appropriate information for its products and strategies and develops technology for its products, services and processes with this information. Therefore, it must be acknowledged that innovation is a strong link between technology and competitive advantage.

The link between innovation and competitive advantage forces businesses to invest in technology to survive among their competitors. Enterprises that cannot see this effect of innovation today may fall behind their competitors and be driven to extinction. Therefore, innovation also has an impact on the economy in terms of not ensuring the continuity of initiatives. Taking into consideration all these effects, innovation is a significant resource for both economies and businesses (Hadjimanolis 2000, 236).

Innovation, which has such a positive impact, has also become an important tool for companies. However, although companies aim to innovate, sometimes their existing resources and knowledge may not be suitable for this realization. For example, even from a single innovation hub affiliated with the Tanzania Commission for Science and Technology (COSTECH), 15 companies received mentorship between 2011-2019 (Mwantimwa 2021, 39-63). As in this example, programs that build bridges between companies and government policies occupy an important position. There are also many communities created by these many programs. It is possible to describe these communities as the community of practice.

2.2 Communities of practice

The community of practice (CoP) is formed when experts from different or similar fields who have similar competencies about a theme come together by setting a common goal to solve the problems related to this theme (Wenger, McDermott and Snyder 2002, 33). This participation of community members includes four different key components. These are meaning, practice, community, and identity, and Wenger (1998) emphasizes that these concepts are characteristic features of social learning theory (Wenger 1998, 145). From the innovation side, CoPs are critical to the emergence of innovation and can be a very powerful potential to generate competitive benefits (Habash 2019, 1505). In addition, CoPs are a basis of the leading applications or projects in organizations with social priorities, as they provide information sharing (Al-Ghamdia and Al-Ghamdia 2015, 406-407). When we consider all these features, common purpose, belonging, collaboration, and knowledge-sharing are the basic concepts of CoPs. In this context, it has become an important issue to examine such communities, and there are several research methods, including social network analysis.

There have been studies in the literature examining various communities of practices. For instance, the impact of Innovation Centers on knowledge, innovation, and entrepreneurship ecosystems in Tanzania has been analyzed with thematic analysis as a community of practice (Mwantimwa *et al.* 2021, 39-63). There are also a community of practice for which quantitative analysis are made and the Social Network Analysis (SNA) technique is mainly used. The Mental Health-Education Integration Consortium (MHEDIC), a practice community, consists of members of young people and their families, educators, and mental health professionals working in their schools, and deals with educational protocols through interdisciplinary collaboration. SNA techniques have been applied, focusing on the six different types of collaboration activity (cited, co-authored, wrote grants, met professionally before the program, mentor/mentee relationship, presented research) in this community of practice which are used as actors of the community for SNA implementation (Lockhart 2017, 152-175). Another study applied social network theory is to analyse the social segregation of Aboriginal and non-Aboriginal people in the region, using data from the city's volunteers and representatives from a number of local government and non-governmental organizations in a suburban neighbourhood in the North of Australia (Ennis and West 2012). Finally, a study examines ways to utilize outcome-based learning to enable the development of Virtual CoP (VCoP) competencies that bridge the service of innovation to enable knowledge sharing and transfer (Habash 2019, 1504-1511).

As it can be seen, various community of practices has been examined with various techniques; Social Network Analysis is a special technique to analyse the network quantitatively. Although social network analysis has been used in other studies, it has been of limited use. A comprehensive and descriptive analysis of innovation communities is valuable in understanding the characteristics of these innovation communities of practices. When an innovation mentor community of practice is considered as a network, applying social network analysis can provide important outputs for both the literature and the sector. In this context, important studies on the subject in the literature are summarized in Table 2.2 below.

Table 2.1. Summary of Literature Review: The table summarizes the related works in the literature.

Relevant Papers	Focus of Research	Research Approach	Key Outcomes	Relevant Open Research Issue
(Cantner and Graf 2006, 463-480)	R&D based collaborations with Patent Data.	SNA was used to understand the change of the network among the years, also to understand difference between different actors.	Innovative mass is necessary for any technology to survive in a local system.	Developing a specific SNA measurement for the structure of the CoP
(Yao *et al.* 2016, 98-107)	Scientific innovation and technological achievements with Co-Citation data.	SNA was used to understand the network, component and centralization analysis have been made.	The average collaboration degree of the scholars of the six disciplines is relatively low, information science is the highest one.	Measuring the connectedness and analyzing actors as members not paper types.
(Lockhart 2017, 152-175)	Analyzing an interdisciplinary collaboration in a CoP	Social Network Analysis to determine the interdisciplinary collaborations along centrality measurements.	An interdisciplinary collaboration is generally based on scientific-based and community cannot maximize	Measuring the connectedness of a interdisciplinary community of practice

			collaboration opportunities.	
(Giusti et al 2020, 20-28)	Information leaks in open innovation networks including many actors(firms, research centers, makers).	SNA was used for analysis, degree, strong and weak components are analysed with SNA.	Makers can be an important source of information leaks.	Community structure-based SNA implementati on
(Mwantimwa *et al.* 2021, 39-63)	Innovation hubs in the co-creation and diffusion of innovation and malfunctions in hubs' operations.	Thematic analysis was used to discover the thoughts of the members of all units of the innovation center.	Innovation centers directly and indirectly affect the co-production and transfer of innovation.	Qualitative analysis of an innovation community
(Meisel *et al.* 2021, 1341-1364)	Analysizng the structure and knowledge sharing networked universities that represents as an innovation community	SNA analysis are used to understand to network structure and knowledge sharing	Red Mutis benefits from the strong knowledge and experience of the regional and international universities that make up the network.	Network is examined between departments not members
This Research	Analysing connectedness and competency attributes of	Content-specific, component and Jaccard similarity analysis	Interdisciplinary work among mentors.	Better quality data is needed.

	innovation mentor community of practice	applications within the scope of SNA techniques.	

2.2.1 Social network analysis 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, 197). There are many types of innovation networks in which organizations interact, such as regional inter-industry networks, international strategic technological alliances and, professional inter-organizational networks, supplier-user networks (DeBresson and Amesse 1991, 363). It has become necessary to examine these networks, which stand and exist at a critical point for both companies, industries, and the economy. The methods of examining these networks, which stand at a critical point, are just as essential.

Social Network Analysis is a technique often used in the field of innovation networks (Alberti and Pizzurno 2015, 268). The SNA is simply composed of two basic elements, where actors (nodes) are connected to each other by ties (edges) (Ennis and West 2010, 408). The main purpose of social network analysis is to accurately measure and show structural relationships. Consequently, SNA leads to enable the examination of natural patterns formed through relationships among members of a community (Lockhart 2017, 152-175). Visuals created through nodes and edges also provide a broad perspective of the network. This structure of SNA has been found suitable for many innovation networks before, and analyses have been made using this technique. One of these studies tried to answer knowledge sharing with the usage of Social Network Analysis have been on patent data of Germany Jena city (Cantner and Graf 2006, 465). 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 analysed with the SNA technique to measure scientific innovation and technological achievements and collaborations (Yao *et al.* 2016, 98-107). Moreover, with the three types of knowledge (technological, managerial, and market knowledge) and five types of brokerage roles (coordinator, gatekeeper, liaison, representative, and consultant), Social Network Analysis is applied to the aerospace sector data (Alberti and Pizzorno 2015, 258-287). In another study, one of the networked universities (NU) with objectives such as innovation, cost savings, strategic network solutions, and which includes knowledge sharing among its actors and highly specialized competencies, was examined. It has been the main objective of the study to characterize one of the NU's network cooperation and integration structure (Meisel *et al.* 2021, 1341). However, as the previous study mentioned, individuals do not appear as nodes in this study. In these studies, instead of examining information sharing between individuals, sectors, institutions, or units are used as actors. The last study is about analysing knowledge sharing in the production industry with SNA techniques according to the information from experts about the deficit of competencies. In other words, these competencies implemented as actors of the network to analyze the deficit while innovative methods and tools are applied to improve production processes (Gudanowska *et al.* 2018, 65-74).

While these studies are valuable for understanding innovation networks, they are not particularly addressing the idea of connectedness for innovation communities of practices. It should be noted that CoPs are different from a community of interest. While the members of a CoP are practitioners however, actors of community of interest are not. In other words, the community of practice members takes some collaborative action, and with the help of these common actions, they develop a common usable repertoire of resources which can be experiences, tools, stories, and ways to address repetitive problems (Wenger and Trayner 2015). Applying social network analysis for a community of practice is a precious approach. In the concept of community of practice, social network analysis is a technique that can provide a comprehensive introduction and analytical result for the measurement of the community. The reason these stated data are not counted as a community of practice is that all actors do not display collaborative teamwork in line with a common goal and target and they do not have any practice according to this goal.

2.3 Social Network Analysis

The network concept can be defined as a collection of connections between elements of a system. The elements of this system connect to each other with some relationships, and these relations change as the system changes. Networks are the form of organization of complex systems in nature and society (Dijk 2006, 2). From the Network Science perspective, a network can be represented as a graph model that shows the relationship between the elements that generate social, biological, technological systems as a network. The human body, school friendships network, metro network, mail network, and mobile networks are the systems that have proper structures for network analysis. Being able to analyze these structures as a network involves a series of historical processes and their connections. A common example of the definition of the network concept concerns the use of the seven bridges over the Pregel river in the city of Konigsberg by the mathematician scientist Leonhard Euler. Euler has developed a theory that travels in the use of bridges cannot be possible without using a bridge more than once, and this theory is supported by Graph theory. Thus, Graph theory forms the basis of social network analysis. Considering the past uses of social network analysis, the underlying basic approach is graph theory. This mathematical theory originated as a way of representing any structure as a configuration of vertices and lines. While vertices, that is, individual points, can be defined in terms of local connectivity structures and centrality in networks, all networks can be defined in terms of overall intensities and partitions into cliques and other clusters. This mathematical approach has also created an application area for other fields (Crossley, Prell and Scott 2009, 2).

Relationship patterns that include a series of actors and the connections they create are called social networks (Carolan 2013). It is seen that the terms network and social network are often used interchangeably. One can argue that the concept of social networks has a wider scope than the concept of networks when the subject is concerned about human relationships. Social network analysis focuses on uncovering patterns of people's interactions. From one perspective, an individual's lifestyle is largely related to how that individual is connected to the wider network of social connections. Moreover, many believe that the reason for societies and organizations' success or failure generally depends on the pattern of their internal structures.

After defining the social network as a finite set or sets of actors and the relations defined on them, it is stated that the social network has three basic elements. These are the actors, the individual attributes of the actors, and the links that define at least one relationship between the actors, respectively. Taken together, the social network perspective is concerned with the structure of relationships and its impact on individual or group behaviour and attitudes (Carolan 2013). The structural approach based on the examination of the interaction between social actors in social sciences is called social network analysis (Freeman 2004, 2). Social actors here can be individuals as well as concepts that contain sociological facts such as international relations, groups or organizations. The relationships that social network researchers' study are often those that bind individual people together because it is stated that besides individual characteristics, relational ties or social structure are essential for a full understanding of the phenomenon.

2.3.1 Innovation communities of practices analyzed by SNA techniques

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 inter-company (Schmitz and Strambach 2009, 232-234). Because in some cases, the daily routine and in-house bureaucracy both prevent a broad perspective, and while some competencies are sufficient for the routine flow of the firm, they may be lacking on the basis of project and strategy. Firms also collaborate to obtain research and acquire new technologies that serve their purpose, complementary skills, and divide risks (Mowery, Silverman and Oxley 1998, 508–509). In order to meet these needs of companies, many innovation centers and communities have emerged. These communities are becoming important mechanisms for the transfer of technology and knowledge (Hooli, Jauhiainen and Ladhe 2016, 61-62). Stated mechanisms can be called communities of practice.

SNA technique has been used in some different types of community of practices. However, there are limited studies that both use innovation community of practice data and examine this data with Social Network Analysis. One of these studies tried to answer the examining leaks in the open innovation community of makers (Giusti *et al.* 2020, 20-28). Although this study examines the innovation community of practice, it focuses on knowledge leaks while separating the network into three different knowledge types (managerial, market and technological) and examines the number of members belonging to knowledge type. In addition, it reflects a more complex network as it is data found by both companies and makers.

The review shows that, while there are some studies examining innovation networks, few of them analyze the innovation mentor community of practice by SNA techniques in the context of connectedness and preferential attachments. Moreover, existing studies in the literature generally made inferences from the outputs of the network, advanced analyzes are limited. So, based on the literature, it is deduced that the connectedness of an innovation community of practice has not been analyzed by the method used in this study. Also, the analysis of preferential attachments by attributes that may have a significant impact on the connectedness of the community is limited. In this context, some of the main motivations of this study are to examine the connectedness and preferential attachments of an innovation community of practice with social network analysis, which can be considered a different approach to the literature.

2.3.2 Knowledge sharing in practice

The practice section, which is the second basic component of the community of practice, is made possible through collaborations in the context of knowledge sharing, which can't be made without competencies. According to Filipowicz (2011), 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 community of practice or networked collaborations, as mentioned earlier, using different techniques and applying these techniques in different contexts. However, these applications either do not include the community of practice or examine knowledge sharing, which is the content of practice, the actors of networks based of only on shared outputs (collaboration type, department type, paper type, patent type) and members of the community not considered. Therefore, examining the collaborative knowledge sharing of an innovation community of practice mentors with technical methods seems to be a subject that has not yet been fully addressed in the literature.

This issue can be explored by examining SNA techniques as a network of community of practice of mentors' collaborations, with competency attributes, when we gather the points of overlapping data from scholars' work. Therefore, knowledge sharing is examined by sharing competencies. Although there are knowledge-based actor-focused studies to examine it (Giusti *et al.* 2020, 20-28), the very idea of network is missing For instance, Giusti *et al.* (2020) developed an occupation recommendation system for students who do not have sufficient knowledge of what skills and abilities are needed for a particular occupation/branch guide us for a technical treatment. In that study, Cosine, Jaccard, Intersection, Euclidean, and Pearson similarity methods were employed. Although Pearson is the most efficient according to the study, the implementation was not for the binary data (Ochirbat 2018).

2.3.3 Similarity techniques

Similarity techniques are frequently used methods to understand many pattern recognition problems (Cha 2007, 300). Barcode recognition, voice recognition, fingerprint recognition, and DNA identification are just a few of them. Therefore, similarity techniques are used for the recognition and interpretation of data in many different structures. One of them is binary data. Jaccard, Dice, Sokal-Sneath, Cosine, and Simpson similarities are the most commonly used methods when determining similarity scores of binary data (Kim, Ikuko and Zhang 2022, 694). Collaborative Filtering (CF) is known as a method of examining binary data. CF systems are based on a scoring principle in order to determine the common interests of users within the framework of certain items (Bilge, Kaleli and Polat 2010, 299).

The last research question of this study was "Can the correlation of collaborations be determined according to the competencies of the mentors?" and CF methods seem to be appropriate to solve this question. Because mentors who have collaborated have competencies within a certain list, can individually have some competencies, while can not have the other competencies. Also, collaborated mentors may have common competencies, opposite competencies, or competencies that are on the list but that the two collaborating mentors do not possess. Bilge *et al.*(2010), mentioned that binary vectors also have these match principles, and calculating linear correlation or measuring the angle between two vectors is not appropriate in the case of binary data.

Among 15 different similarity methods, a number of scholars working with compound identification and using binary data found that the Jaccard similarity method is one of the three best (Kim, Ikuko and Zhang 2022, 694). The other study that worked on collaborative filtering that uses binary data found that Jaccard and Dice measurements provided the best outputs (Bilge, Kaleli and Polat 2010, 299). In this study, due to the good results of Jaccard Similarity and the fact that the competencies that the mentors do not have in common (both mentors do not have the competency), they do not create a similarity. We decided to choose Jaccard Similarity, where we can measure the competencies that two mentors can have in common and the competencies they have in contrast (one has competency while the other is not). Jaccard Similarity's binary competency fingerprint and its application to a mentor network are explained in the method section. Although there are many valuable studies dealing with similar issues in the literature, there has not been any study dealing with this method, so this study can be considered original.

3. CHAPTER/METHODS

3.1 Data Acquisition and Preparation

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 program to support organizations for establishment of corporate innovation systems. Those in this group can mentor one or more companies, but only the relationships between mentors are examined for this study. 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 the institutions that they work in, their titles in that institution, and the competencies of these mentors. All this information helped a visual printout of the network and a detailed analysis.

Social Network Analysis methods and techniques are used to examine the connectedness and preferential attachments and lastly integrated with Jaccard similarity to discover knowledge sharing. The scope of our analysis is based on a self-reported data of 28 innovation mentors and we use the data as anonymous. In Social network theory, a network contains nodes that may or may not be connected to each other (Graf 2017, 6), 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. Table 3.1 shows the example version of mentioned node list and Table 3.2 also shows the example version edge list except for the column headings for both tables that represent the original headings. 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.

Table 3.1. Node list of Mentors: The node list is an example version of the actual node list. Column headings are the exact ones as the actual list, however, mentor information just represents the example and length of list changes according to the number of mentors

Mentor ID	Title	Institution	Competency 1	Competency 2	Competency 3	Competency 4	Competency 5
M01	Manager	Company X	C3	C8	C9	C10	C15
M02	Dr.	University X	C2	C4	C7	C10	C21

Table 3.2. Edge List of Mentors: The edge list is an example version of the actual node list. Column headings are the exact ones as the actual list, however, mentor information just represents the example and length of list changes according to the collaborations.

Source	Target
M01	M12
M01	M25
M02	M20
M02	M23

All members of a network may not 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 Giant Component (GC) (Aydin and Perdahci 2019, 231). In order 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.

When GC emerged, all analyzes 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 in the context of their competencies.

After the data were collected, the work was continued with the visualization to understand the structure of the network. Much software is available for analyzing social network data and visualizing analysis results. Some of these software applications are used for commercial purposes, while others are used free of charge. The most used social network analysis software are Ucinet and Netdraw (for visualization purposes), Pajek, Gephi, Graphviz, NodeXL, and R programming language. In addition, the Python programming language is also used in social network analysis studies. We used Gephi for visualization and centrality measurements and R statistical language for other analyses. The visualization process firstly started with creating edge and node lists, then transferred to Gephi, which is open-source software that allows for visualization and discovery of all types of networks (Gephi 2010). All the components emerged with this visualization stage. Then, GC was detected, and new edge and node lists were created according to the GC.

3.2 Modeling the Network

In this study, the network is created from nodes that represent mentors and edges that represent the collaboration of these mentors. The collaboration of mentors gathered from self-reports, and one can expect that not all collaborations are reciprocal. In this regard, the network is created as a directed network. The directed network includes all in and out edges that a node has. There are three types of possible edge direction. If there is only a one-sided connection, there is an arrow pointing from the connecting node to the connected node and that can be also oppositely. Also, edge directions can be reciprocal. In undirected networks, the edges do not point in any direction. Figure 3.2 shows an example about a directed mentor network.

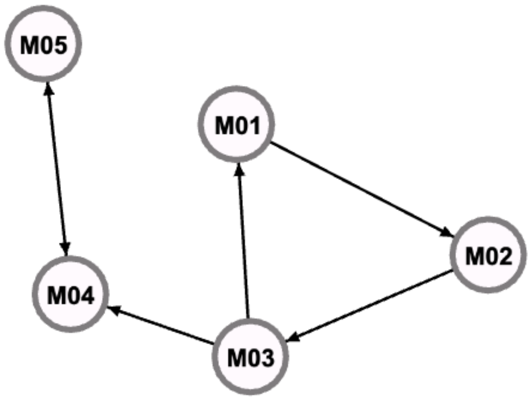


Figure 3.1. Example of Directed Graph: The figure shows an example of a directed graph with five nodes and six edges. There is a reciprocal relation between nodes M04 and M05.

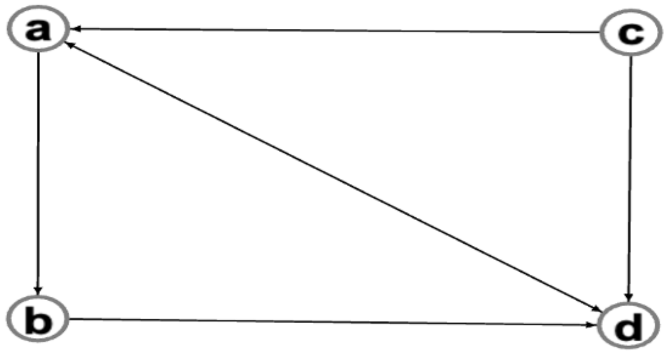
Similar to the example in Figure 3.2, after the real whole network of innovation mentors was created with the help of Gephi according to the node and edge list, the GC appeared visibly, and the analyzes were made based on the comparison of the GC and the whole network. Firstly, centrality measurements were done to understand the key actors of the network. Also, the iGraph package was used in R Statistical Language to calculate the assortativity, reciprocity, and transitivity measurements.

3.3 Social Network Analysis and Basic Concepts

One of these fundamental measurements in SNA is a centrality concept, which can be measured to identify the key nodes in the chosen network. Degree, closeness, and betweenness are the most commonly used measures in social network analysis.
Social network models can be represented in three
ways.
1. G = {(ni, nj)} List element groups and their interactions using a mathematical notation in the form of Here G is the network name and (ni, nj) is the node pairs.
2. A diagram or graph representing the nodes and edges of the network.
3. A matrix with N × N entries representing the number of connections between pairs of nodes in the network when N is defined as the number of nodes. The mathematical representation in Figure 3.3 shows a social network with four nodes described using a diagram and a matrix.

a) G = {(a, b), (a, d), (b, d), (c, a), (c, d), (d, a)}

b)



c)

	a	b	c	d
a	0	1	0	1
b	0	0	0	1
c	1	0	0	1
d	1	0	0	0

Figure 3.2. Network Representations: A represents the list form of the network, b represents the graph form of the network and lastly, c represents the adjacency matrix of the network.

3.3.1 Reciprocity

In a network, reciprocity is a measure of how mutually the members cooperate. It is a measure of whether the connections between the nodes are mutual, that is, two-way. This metric, which is used only for directed networks, is expressed by the phrase, “if you follow, I will follow”. Reciprocity is found by dividing the number of reciprocal node pairs in the network by the maximum possible reciprocal node pairs.

3.3.2 Transitivity

Transitivity is the reciprocity of tripartite relations. One of the criteria used in the analysis of edge-forming behavior is transitivity. If transitivity is explained from A, B, and C, three separate nodes form the network; If there is a B-C linked to each other while there are also links in between A-B and A-C, it means that there is a transitive behavior between these nodes.

3.3.3 Bridge

It is defined as a link or edge that causes the endpoints of the network to change when deleted from the network. In other words, causes the network to be disconnected. It can also be defined as the concept that increases the number of connected components in case of deletion.

3.3.4 Components

They are groups of interconnected nodes in a social network. If the entire network is interconnected, there is only one component.

3.3.5 Centrality analysis

One of the main purposes of social network analysis is to identify nodes that are important for the extension of their relationships with other nodes in the network. In other words, centrality seeks to understand the importance of nodes and relationships in social networks. It is a measure of the intensity of an actor's relationships with other actors. For example, it is considered to be as important as a node is in a central location in the network and in an important position in the information flow. Centrality is an indicator of a node's social strength based on how well they connect the network (Kosorukoff 2011, 6).

One of the most used centrality measurements is degree centrality. The degree centrality can be defined as the simplest measure of centrality. Degree centrality is calculated by the number of connections a node has. A node's rating can be calculated without knowing the entire network they are connected to. Depending on the type of the network, degree centrality can be interpreted in different ways. If the network is undirected, then degree centrality depends on just existing edges. Basically, a node that has the highest number of connections has the highest degree. However, for the directed graph, a node can have in-coming edges and out-going edges. The total of incoming edges of a node named in-degree and the total of out-going edges of a node named out-degree.

The other most used centrality measurement is betweenness centrality. The 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, 188-191). It's based on the shortest paths in a network. The interval is calculated by adding how many shortest paths pass through each node.

3.3.6 Assortativity

Assortativity is the measurement of whether the relationship between higher-degree nodes and other higher-degree nodes is established (Newman 2003, 5). In short, it provides the numerical expression of the question of whether members are affiliated with each other with similar members or are members actively avoiding members similar to themselves. Therefore, the same calculation is used to measure the attributes rather than degree assortativity, so the tendency of individuals to cooperate with a similar title and institution attributes was calculated with the iGraph package in R. Assortativity calculation is specified in the Equation 3.1 below.

$$r = \frac{\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right) x_i x_j}{\sum_{ij}\left(k_i \delta_{ij} - \frac{k_i k_i}{2m}\right) x_i \, x_j} \tag{3.1}$$

To summarize briefly, δij represents the Kronecker delta. The k represents the degree, and the m represents the number of edges in the network. As a result, this coefficient can take values between 1 and -1. A value of 1 indicates the preferential attachment of members with the same degree, a value of 0 indicates that there is no preferential attachment, and -1 indicates the preferential attachment of members of opposite degrees.

3.4 Jaccard Similarity Binary Implementation

Different methods were used to measure the level of correlation of the similarity of competencies when the collaboration of this innovation mentors' network. The first 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, according to whether they have 26 competencies, and then to find fingerprinted similarity in advanced stages. This similarity was measured with the matching competencies between two mentors and Jaccard similarity for binary implementation was created by writing R Script and shared in Appendix A.2.

To calculate the Jaccard Similarity between nodes that are connected with an edge, there is a need for a fingerprint. The fingerprint of nodes is simply an array of 26 numbers that includes just 1's and 0's. As shown in figure 3.4, the columns are created to correspond to competencies and the rows 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 mentor was created. According to the fingerprint, it is 1 if there is a corresponding competency and 0 if it does not.

	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	0010000111001000000000000000
M02	0101000000000000011010000000
M03	0000000001010000010000011000
M04	0000000000000000000000000000
M05	0000000000000000000000000000

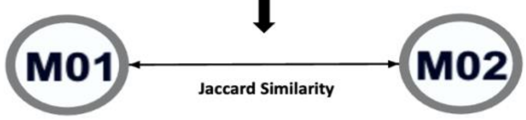


Figure 3.3. The Fingerprint Example: The example shows the process of competency fingerprint creation.

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 stated in equation 3.2 below;

$$J(i,j) = sim(i,j) = \frac{TP}{TP + FP + FN} \tag{3.2}$$

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, which is one of them has the competency, and the other does not, and also 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. CHAPTER/FINDINGS AND DISCUSSION

4.1 Findings

4.1.1 Connectedness calculated with SNA techniques

Examining the connectedness analysis will firstly depend on the entire network in general and then benchmark with the GC. The whole network has 4 components, and one of them is visibly large. If the total nodes in the first-largest component are more than fifty percent 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, 231). As shared in Table 4.1 the Giant Component constitutes 71% of this network and most of the community belongs to a group that can interact. Its shown in Figure 4.1 that each component is colored differently and the GC is colored green and labeled as a Component 0. So, GC consists of Component 0 only, hence Component 0 will be named as GC from now on. Also, Table 4.1 shows that the number of nodes of the whole network is 28, while the number of GC nodes is 20. It is also a component that holds the majority of connections with the 31 edges, while the whole network has 36 edges. At this stage, in order to understand the connectedness of the network, all the following explanations will be based on benchmarks.

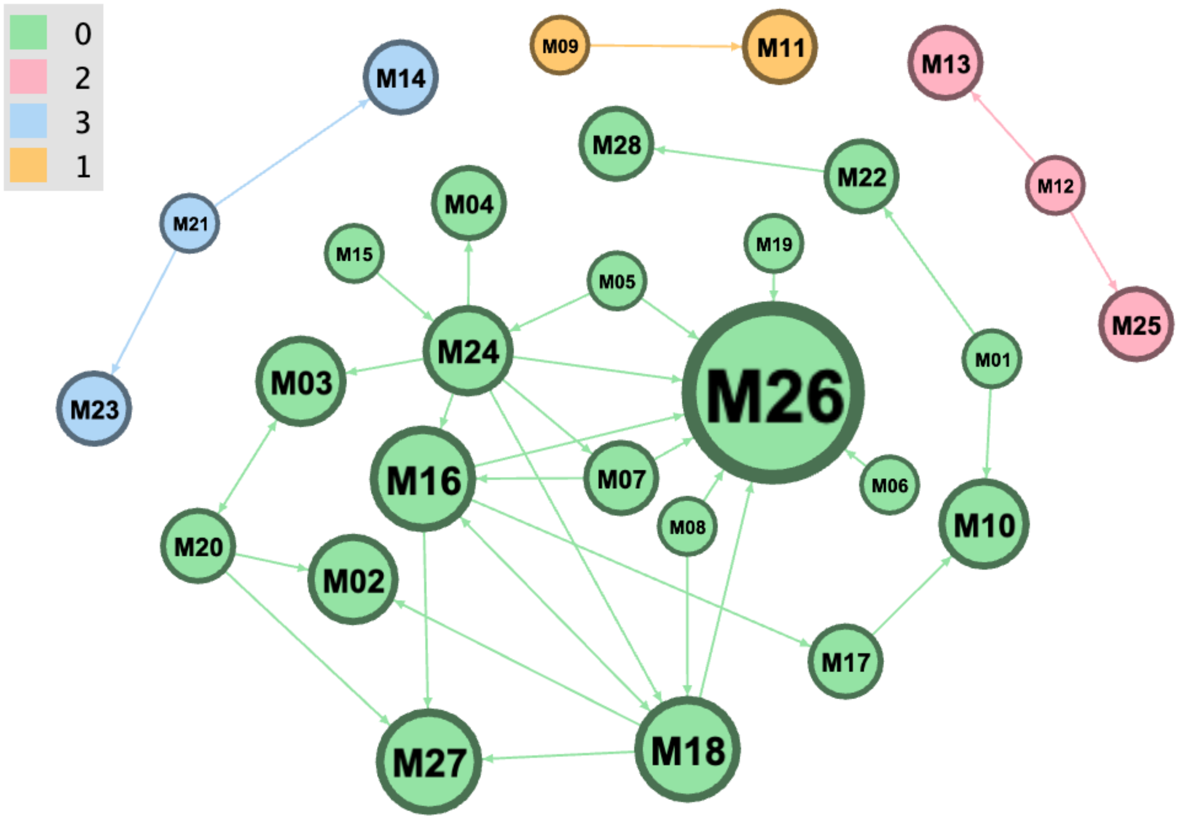


Figure 4.1. The Mentor Network: The size of the nodes is arranged according to their in-degree value, with the largest node having the highest in-degree value. The colors show which component it is included in, and nodes in the same component are shown with the same color and each color represents a different Component ID that is scaled between 0 to 3.

Table 4.1. Social Network Analysis of Mentor Network: The table summarizes the SNA measurements of the Whole Network and GC separately.

	Whole Network	Giant Component
Number of Nodes	28	20
Number of Edges	36	31
Number of Components	4	1
Giant Component	0.71	1.00
Average In-Degree	1.29	1.55
Average Out-Degree	1.29	1.55
Average Degree	2.57	3.10

Average Path Length	1.78	1.84
Average Closeness Centrality	0.47	0.51
Average Betweenness Centrality	0.00	0.01
Degree Assortativity	0.00	-0.11
Reciprocity	0.11	0.13
Transitivity	0.28	0.29

The size of the nodes in Figure 4.1 was determined according to the in-degree of the mentors. As stated in table 4.2, M42, which has been declared to collaborate with eight different people, can be said to have the highest number of in-degrees and is an essential node for this network. The average in-degree and out-degree measurements are equally separated for both network, which are measured as 1,29 and 1,55 for whole and GC, respectively. The Average Path Length of the whole network is 1,78, and the average degree is 2.57. The average Path Length and degree of GC rise to 1,84 and 3,10, respectively. The assortativity of GC is -0,11 as shared in Table 4.1, and this shows that some high-degree mentors collaborate with low-degree mentors. For the whole network, mentors don't have any preference according to the degree as the measurement is close to zero with a value of 0.00. While the reciprocity value is 0.11, the transitivity value is 0.13; it is possible to say that tripartite relations are more robust than bilateral relations and also close numbers valid for the Whole network too. While 3 people collaborated with only one person in this network, one person declared that they collaborated with eight people; top-degree measurements can be seen in Table 4.2.

Table 4.2. Network centrality analysis of GC: The table shows the stated measurement for each node of GC.

ID	Betweenness Centrality	Degree	In-Degree	Out-Degree
M24	0.06	8	2	6
M16	0.05	7	3	4
M18	0.03	7	3	4
M17	0.02	2	1	1
M03	0.01	3	2	1

M20	0.01	4	1	3
M22	0.00	2	1	1
M26	0.00	8	8	0
M27	0.00	3	3	0
M07	0.00	3	1	2
M02	0.00	2	2	0
M10	0.00	2	2	0
M01	0.00	2	0	2
M05	0.00	2	0	2
M08	0.00	2	0	2
M04	0.00	1	1	0
M28	0.00	1	1	0
M06	0.00	1	0	1
M15	0.00	1	0	1
M19	0.00	1	0	1

When we look at all the measurements, we observe that they are close to each other. The most dramatic differences were in all type of average degree and degree assortativity coefficient measurements. Although there was a GC of 0.71 in the innovation mentor community of practice, bilateral and tripartite collaborations could not make a significant difference compared to the whole network and remained at a low level of 0.13 and 0.29. 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 1, the mentor with the highest connectivity is M26 and is visualized as the largest node. However, M24, with the highest betweenness centrality, which is 0.06, has a critical position for the shortest paths of the GC, and in the absence of M24, even some mentors become unreachable. The same can hold true for M16, which is the second highest position with a value of 0.05 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.

4.1.2 Preferential attachments by assortativity coefficient

Measurements of the assortativity of the attributes allow us to see the preferential attachments of the GC and the whole network while collaborating. As seen in Table 4.3, the values of Assortativity measurements for GC and the whole network are different. In GC, some high-degree members avoid members with high-degree mentors, whereas in the whole network, it is not observed that the mentors collaborated according to the degree.

Table 4.3. Assortativity Measurements by Attribute Type: The table shows each attribute assortativity coefficient for the GC and the Whole Network separately.

Attribute Type	Giant Component Assortativity Coefficient (r)	Whole Network Assortativity Coefficient (r)
Degree	-0.11	0.00
Institution	-0.01	0.00
Title	0.00	0.03

When we look at all assortativity values, the ratios are quite low and zero or close to zero, and in between -0.11 to 0.03, as shared in Table 4.3, except the GC degree assortativity coefficient. This indicates that the attributes shared in Table 4.3 in the collaborations of the mentors are not a priority and are non-assortative. However, we must exclude the value of GC degree assortativity relative to the denominator because it is negative and shows a higher ratio of -0.11 rather than other measurements. From this value, it can be said that some mentors in GC collaborate with dissimilar mentors in terms of degree. Another inference to be made from this table is the importance of examining the GC and the whole network separately. While degree assortativity is negative (-0.11) for GC, it is 0.00 for the Whole network, and it shows a non-assortative property. Also, even the assortativity coefficient measurements of institution attribute, are close to zero or close to zero; they show the opposite property -0,01 and 0,00 for GC and the whole network just as opposite in degree attribute for the -0.11 in GC and 0.00 for whole network, respectively. According to these results, mentors do not make preferential attachments according to a certain attribute, but in GC, very few of the mentors collaborate with mentors with different degrees from them.

4.1.3 Jaccard similarity

As mentioned in the connectedness of the innovation mentor network section, connectedness affects analysis results. While most results are close, in particular, the assortative coefficient measuring mentors' collaborative preferential attachments by degree attribute is disassortative in the GC and non-assortative in the whole network. These assortativity coefficients are calculated with the labels or values assigned to the nodes (igraph.org, 2022). If a node (mentor) had only one competency, it would be possible to calculate the preferential attachments of the competency attribute in this community of practice. 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. Because mentors are affiliated with an institute and also collaborate with companies in their mentoring projects, they have both academic and field competencies. As shown in Table 4.4, its frequency is evenly distributed, and the distribution of type is almost equal.

Table 4.4. Competency overview of GC: The table shows the number of competencies and their frequency that mentors have for academic and field type separately and than the total of them.

	Academic	Field	Total
Total Number of Competency	14	11	25
Total Frequency	49	48	97

Moreover, in Table 4.4, it can be seen that a total of 25 different types of competencies have been identified, 14 of which are academic and 11 are field competencies. Table 4.5 shows the frequency of stated competencies.

Table 4.5. Competencies of GC Members: 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
F_Technology Map	7
A_Digitalization	6
A_Innovation Culture	6
A_Market Research	6
F_Market Research	6
F_Design Oriented	6
F_Innovation Culture	5
F_Project Management	5
A_Branding	4
A_Project Management	4
A_Technology Map	4
F_R&D Processes	4
F_Digitalization	4
F_Intellectual Property Rights	4
A_Lean manufacturing	3
F_Change Management	3
F_Branding	2
F_Data Analysis	2
A_Change Management	1
A_Foreign Trade	1
A_Intellectual Property Rights	1
A_Organization Development	1
A_Supply Chain Mng.	1
A_Data Analysis	1

The design-oriented competence, which was declared to be owned by 9 mentors, was the type of competence held the most as shown in Table 4.5. 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 10 (32%) of 44 collaborations, they do not have any competencies fully common, and 9(29%) just have one common, as shared in Table 4.6. There is only 1(3%) collaboration with a maximum of 4 competency matches in total. At this point, Table 4.6 shows that mentors collaborate more with the ones that have fewer common competencies with them. However, if we consider that 6 of the participants do not share their collaborations, 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 4.6. 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 3% of all collaborations.

Table 4.6. Collaborations by Competency Measurements of Network: The table shows each edge Jaccard similarity by the competencies of source and target nodes.

Source	Target	Competency Match	Jaccard Similarity
M24	M04	4	0.67
M05	M24	3	0.43
M06	M26	3	0.43
M16	M17	3	0.43
M03	M20	2	0.25
M07	M26	2	0.25
M08	M18	2	0.25
M08	M26	2	0.25
M16	M28	2	0.25
M18	M26	2	0.25
M07	M16	2	0.25
M16	M26	1	0.11
M18	M02	1	0.11
M20	M27	1	0.11
M24	M03	1	0.11

M24	M07	1	0.11
M24	M16	1	0.11
M24	M18	1	0.11
M24	M26	1	0.11

The GC weighted according to the Jaccard Similarity scores is shown in Figure 4.2. A thick edge represents high similarity, and that means the significant number of competencies are the same. According to the Jaccard Similarity measurements, the average of Jaccard Similarity is 0.16. This means that mentors are looking for interdisciplinary collaboration. Members of this innovation mentors community of practice collaborate more with mentors with competencies they do not possess.

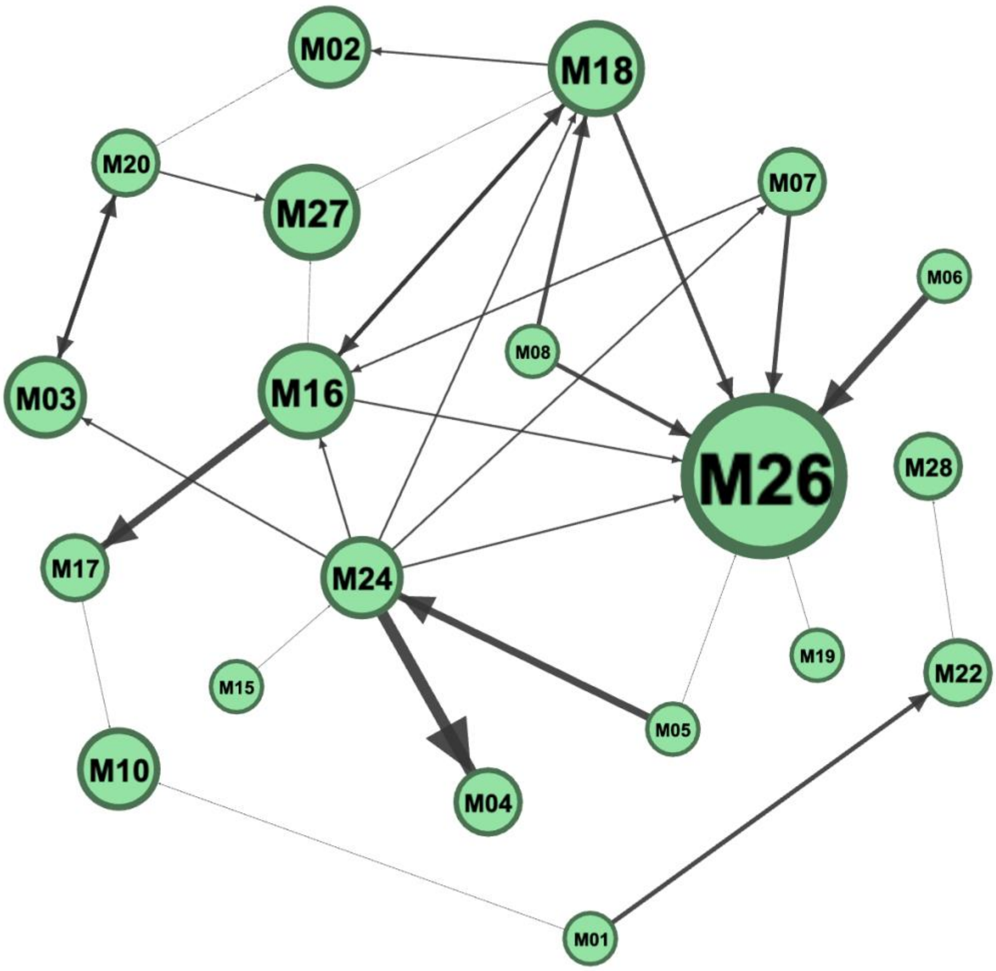


Figure 4.2. Competency Similarity Weighted Mentor Network: The size of the nodes is arranged according to their in-degree value, with the largest node having the highest in-

degree value. The edge thicknesses are weighted according to the Jaccard Similarity scores. The scale of thickness is between 0-0.67.

4.2 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. 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 community of practices of innovation mentors who provide companies with a guidance on the establishment of corporate innovation systems. The community of practices of innovation mentors also contributes to the innovation processes of companies. On the other hand, they are in the same community with many mentors from different sectors and competencies, and they are in a unique mechanism of knowledge exchange of different sector information, methods, and technologies. These communities of practices are like a bridge in the diffusion of innovation. This diffusion simply occurs with knowledge sharing of mentors. Thus, innovation mentors' community of practice is unthinkable without collaborations. Because it enables the transmission of practice, experience, and tools among mentors through collaborations. This study emphasizes the gravity of connectedness through the collaboration of mentors and examines the giant component separately, with the differences in measurements and competency-based knowledge sharing of mentors in the context of practice while examining a group of people working for a common goal. In other words, a community of practice that is noted as a network.

In this study, while an innovation mentor community of practice is considered a network, the features that make up the CoP are examined in the context of SNA. This means examining the community under two separate headings. First, the connectedness of the CoP, centered around a common innovation idea, was tried to demonstrate by SNA's component analysis. Because a community of practice exists with a community that can create commitment around a common idea. Also, this feature was supported with assortativity measurements to comprehend possible preferential attachments that can occur in the community and affect the connectedness. Second, the knowledge-sharing features of the community of practice were encoded as a fingerprint on the edge list created with SNA techniques, and the mentors' practice was analysed by examining the competency-based knowledge-sharing with the help of Jaccard Similarity. Because another feature that makes up a community of practice is knowledge-sharing.

The whole network consists of 4 separate components, while the Giant Component stands alone. For this reason, one can emphasize that there may be differences in any analysis that is made and that future research should be done by recognizing the importance of this. Thus, this study provides analytical results for these differences. This innovation community of practice created 71% GC and did not show full connectedness. In order to examine the community to act together toward a goal, it is important to look at its connectedness. This is done by focusing on the Giant Component (GC). Also, to give practical advice, the whole network and GC should be examined separately because when looking at the Giant Component and the Whole Network, their measurement results are different, and they have different network structures. For example, in terms of degree assortativity, the value of the Whole network is zero, while in GC, this value is negative. Additionally, the institution attribute has similar oppositeness; the whole network has a positive assortativity coefficient value, on the other hand, GC has a negative assortativity coefficient value. In other words, while preferential attachment cannot be seen in Whole Network, a minority of mentors cooperate with mentors who are different from their degree values in GC. While examining the knowledge sharing, which constitutes the practice part of the community of practice, since the component differences differ in the other analysis results, the GC that can provide connectedness was examined alone. One of the features that make up a community of practice is that the members are connected along a number of means including regular knowledge-sharing meetings, and online messaging services. This practice is created through knowledge sharing. Knowledge sharing, on the other hand, is the knowledge that is formed and developed by blending the experiences of mentors with the same or many different competencies around their competencies and is shared by collaboration with the knowledge created by other mentors in the same way. 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.

4.2.1 Limitations

In this study, some limitations were encountered in the data focus. These are listed below;

- Data does not change over time, it is static. The data on which all analyzsis are done depends on the date the mentors self-reported. New competencies or connections of mentors developed over time are not evaluated.
- Not all mentors wanted to share their collaboration. Only 18 of mentors shared their collaborations. The data of mentors who do not share can have an impact on the results.
- Competencies are limited to 5. However, mentors can have more than 5 competencies. More comprehensive competency attributes may affect results.

5. CONCLUSION

The study examined the collaborations of innovation mentors as a community of practice through social network analysis. This analysis symbolizes a "snapshot" of patterns that may change over time while the community evolves and mentors change (Lockhart 2017, 166). In this study, when the elements that make up a community of practice are examined from the perspective of SNA, it is aimed to obtain findings with numerical measurements rather than the measures and concepts behind them. Although the network of innovation mentors provided a high level of connectedness (71%), at the meso level (degree of connections at the group level) the expected connectedness may be found inadequate. In addition, although the entire network provides high connectedness, reciprocal (0.11) and transitive (0.28) collaborations remained low. It is aimed to measure the attributes that may affect this with the assortativity coefficient. However, the results indicate that the mentors do not make any preferential attachment according to the node attributes as title, institution. Except, only %11 of the mentors tended to collaborate with mentors with opposite degrees. In this case, it is observed that the existing attributes have no effect on the collaborations. Examining the practice element of the network that makes up the CoP was made possible by implementing the Jaccard Similarity scores of the mentors' competencies into the network analysis. According to Jaccard similarity scores, it makes dissimilar knowledge sharing on the basis of competencies in network collaborations. This suggests that innovation mentors that have dissimilar competencies can be a useful criterion in the selection criteria when recruiting new members of the community of practice. Based on the CoP, 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. In addition, while recruiting new members, mentors with competencies that do not exist in the network may be preferred due to interdisciplinary collaborations.

In the study the innovation mentor community of practice is considered as a network, and therefore, although they have an interest in this field, some do not want to share their collaborations. Therefore, when we started the analysis, only 17 out of 28 nodes shared both their collaborations, which can be a rather low and inadequate number for the clarity of the analysis. There is a potential to carry out follow-up research that aims to study all mentors wish to share their connections and competencies. Thus, one can argue that more richer results can be obtained with more complete data. Also, the members have time dependent attributes. For instance, it is not specified whether the members have recently joined the innovation mentor community of practice. It is another question to determine the threshold value according to the while measuring the collaboration of mentors based on competencies that they have. In order to find answers to these questions, complete data and more attributes should be available and shared. It is also important to emphasize the need for comparative analysis of similar innovation communities that can reveal the impacts of varying connectedness and similarities of competences among members on the performance outcome of community of practice.

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APPENDIX A

R Codes for SNA

```
#installing packages

install.packages("igraph")

library(igraph)

# DATA FRAMEWORK -------------------------------------------------------

#Import csv files

IMN_Edges <- read.csv(file.choose(), header = T,sep = ";")

IMN_Vertices <- read.csv(file.choose(), header = T,sep = ";")

IMN_Giant <- graph.data.frame(vertices = IMN_Vertices, d= IMN_Edges,
    directed = TRUE)

# NETWORK ANALYSIS ---------------------------------------------------

#Access nodes and edges

E(IMN_Giant) #Edges of Graph

V(IMN_Giant) #Vertices of Graph

summary(IMN_Giant) #View the propeties of network

# Assortativity&Reciprocity&Transitivity ------------------------------------

Assortativity <- assortativity.degree(IMN_Giant, directed = TRUE)

Assortativity

ass_for_institution <- assortativity_nominal(IMN_Giant, value_ institution,
    directed = TRUE)

ass_for_ institution

ass_for_title <- assortativity_nominal(IMN_Giant, value_ title, directed = TRUE)

ass_for_ title
```

```
all_assortativity =data.frame(Assortativity,ass_for_ institution,ass_for_ title)

df_assortativity=t(all_assortativity)

Reciprocity <- reciprocity(IMN_Giant)

Reciprocity

Transitivity <- transitivity(IMN_Giant)

Transitivity

transitivity(IMN_Giant, type = c("global"))

trangles_ino <- triangles(IMN_Giant)

matrix(trangles_ino, nrow = 3)

#Table of assortivity, reciprocity, transitivity

nw_only_ino =data.frame(Reciprocity,Transitivity)

IMN_GC_ART=t(nw_only_ino)
```

APPENDIX B

R Codes for Jaccard Similarity

```
#Jaccard Similarity Steps -------------------------------------------------------

#Loading the data, competencies that mentors have represents 1, competencies that mentors have not represents 0
sourceIMN <- read.csv("IMN_S_C.csv", sep = ";")
targetIMN <- read.csv("IMN_T_C.csv", sep = ";")

#Creating function for matching competencies
simple_match <- function(a, b) {
  count <- 0
  for (vall in 1:25){
    if (a[,vall] && b[,vall] == "1")
      count <- count + 1
  }
  print(count)
}

#Making a dataframe for number of matched competencies
mc <- data.frame()
for (jj in 1:31){
  mc[jj,1]<- data.frame(simple_match(sourceIMN[jj,], targetIMN[jj,]))
}
#Loading the data for zero match, competencies that mentors have represents 0, competencies that mentors have not represents 1
ZsourceIMN <- read.csv("Z_IMN_S_C.csv", sep = ";")
ZtargetIMN <- read.csv("Z_IMN_T_C.csv", sep = ";")
#Making a dataframe for number of competencies that did not matched
nmc <- data.frame()
for (jj in 1:31){
  nmc[jj,1]<- data.frame(simple_match(ZsourceIMN[jj,], ZtargetIMN[jj,]))
}
nmcJ= 25-nmc
js_score=mc/nmcJ
```

APPENDIX C

C.1. Node List of the Whole Network

Mentor ID	Instution	Title	Attribute_Competency_1	Attribute_ Competency_2	Attribute_ Competency_3	Attribute_ Competency_4	Attribute_ Competency_5
M01	Near East University	Prof. Dr.	A_Design Oriented	A_Technology Map	A_Project Management	A_Innovation Culture	NaN
M02	Tokat Gaziosmanpaşa University	Prof. Dr.	A_Project Management	A_Innovation Culture	F_R&D Processes	F_Innovation Culture	F_Project Management
M03	Marmara University	Prof. Dr.	A_Market Research	F_Market Research	F_Innovation Culture	A_Innovation Culture	A_Branding
M04	Kadir Has University	Dr. Teach Member	A_Design Oriented	F_Design Oriented	F_Market Research	A_Market Research	F_Intellectual Property Rights
M05	Turkish-German University	Prof. Dr.	A_Lean manufacturing	A_Digitalization	A_Design Oriented	F_Market Research	F_Design Oriented
M06	Tekirdağ Namık Kemal University	Prof. Dr.	F_R&D Processes	F_Innovation Culture	F_Technology Map	F_Project Management	F_Design Oriented
M07	Özyeğin University	Assoc. Dr.	A_Market Research	A_Technology Map	F_Innovation Culture	F_Technology Map	F_Intellectual Property Rights
M08	Pamukkale	Assoc. Dr.	A_Design Oriented	F_Technology Map	A_Project	A_Innovation Culture	F_R&D Processes

	University				Management		
M09	Istanbul Okan University	Assoc. Dr.	A_Digitalization	A_Data Analysis	F_Market Research	F_Data Analysis	F_Digitalization
M10	Dokuz Eylül University	Prof. Dr.	A_Market Research	A_Branding	A_Organization Development	A_Foreign Trade	A_Supply Chain Mng.
M11	Istanbul Okan University	Assoc. Dr.	A_Digitalization	A_Design Oriented	A_Project Management	F_Project Management	F_Digitalization
M12	Eskişehir Osmangazi University	Instructor	A_Intellectual Property Rights	A_Technology Map	F_Technology Map	F_Intellectual Property Rights	F_Design Oriented
M13	Istanbul University	Technology Transfer Office General Manager	A_Ar-Ge Süreçleri	F_Innovation Culture	F_Project Management	F_Technology Map	F_Intellectual Property Rights
M14	Bursa Technical University	Dr.	A_Digitalization	A_Technology Map	F_Project Management	F_Technology Map	F_Digitalization
M15	Istanbul Okan University	Dr.	A_Digitalization	A_Technology Map	F_Project Management	F_Technology Map	F_Digitalization
M16	Kadir Has University	Assoc. Dr.	A_Digitalization	A_Design Oriented	F_Data Analysis	A_Data Analysis	F_Technology Map
M17	Izmir University of Economics	Prof. Dr.	A_Digitalization	A_Design Oriented	F_Data Analysis	F_Design Oriented	F_Digitalization

M18	Tokat Gaziosmanpaşa University	Assoc. Dr.	A_Lean manufacturing	A_Design Oriented	A_Technology Map	F_Project Management	F_Technology Map
M19	Istanbul Kultur University	Instructor	A_Branding	F_Branding	F_Market Research	A_Digitalization	F_Digitalization
M20	Tokat Gaziosmanpaşa University	Assoc. Dr.	A_Design Oriented	A_Market Research	F_Change Management	F_Market Research	F_Design Oriented
M21	Iskenderun Technical University	Research Assistant	A_Digitalization	A_Design Oriented	A_Intellectual Property Rights	A_Technology Map	F_Intellectual Property Rights
M22	Yasar University	Strategic Planning Coordinator	A_Digitalization	A_Change Management	F_Innovation Culture	F_Change Management	F_Digitalization
M23	Yıldız Technical University	Assoc. Dr.	A_Data Analysis	A_Market Research	F_Technology Map	F_Market Research	F_Data Analysis
M24	Istanbul Okan University	Dr.	A_Design Oriented	F_Intellectual Property Rights	F_Market Research	A_Intellectual Property Rights	F_Design Oriented
M25	Çankaya University	Manager	A_Lean manufacturing	A_Intellectual Property Rights	F_Intellectual Property Rights	F_Digitalization	F_Lean Manufacturing
M26	Izmir University of Technology	Dr.	F_R&D Processes	F_Change Management	F_Intellectual Property Rights	F_Project Management	F_Technology Map
M27	Istanbul Okan	Asst. Prof.	F_Branding	A_Project	A_Market	A_Branding	A_Innovation Culture

	University			Management	Research		
M28	Izmir Katip Celebi University	Prof. Dr.	A_Innovation Culture	A_Data Analysis	A_Lean Manufacturing	NaN	NaN

APPENDIX D

D.1. Edge List of the Whole Network

Source	Target	Type
M01	M10	Directed
M01	M22	Directed
M03	M20	Directed
M05	M26	Directed
M05	M24	Directed
M06	M26	Directed
M07	M26	Directed
M07	M16	Directed
M08	M26	Directed
M08	M18	Directed
M09	M11	Directed
M12	M25	Directed
M12	M13	Directed
M15	M24	Directed

M16	M26	Directed
M16	M27	Directed
M16	M18	Directed
M16	M17	Directed
M17	M10	Directed
M18	M26	Directed
M18	M16	Directed
M18	M27	Directed
M18	M02	Directed
M19	M26	Directed
M20	M27	Directed
M20	M02	Directed
M20	M03	Directed
M21	M23	Directed
M21	M14	Directed
M22	M28	Directed
M24	M26	Directed
M24	M16	Directed
M24	M03	Directed

M24	M07	Directed
M24	M04	Directed
M24	M18	Directed

CURRICULUM VITAE

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