J Knowl Econ
https://doi.org/10.1007/s13132-018-0553-x

Complex Network Analysis for Knowledge Management and Organizational Intelligence

Josef Daňa[1] · **Francesco Caputo**[2] · **Jaroslav Ráček**[1]

Received: 10 October 2017 / Accepted: 6 June 2018

Abstract The scope and focus of knowledge management has changed multiple times over the last decades, each shift revealing new challenges to management science. Recent change of perspective drawing from systems thinking is suggesting that knowledge is created through interaction between people. Complex network analysis is a rigorous method that can be used for evaluation of interaction patterns between employees. The literature suggests that specific interaction patterns are related to increased knowledge flow, innovativeness, and performance. Aim of this paper is to provide an overview of various approaches utilizing the complex network analysis in organizations and present suggestions that might support managerial decision-making processes related to knowledge management and organizational intelligence.

Keywords Social network analysis · Complex networks · Network science · Knowledge management · Knowledge flow · Organizational intelligence

Introduction

Organizational learning is one of the key topics covered by managerial theories as it is tightly connected to the performance and the ability of a company to success on the

✉ Josef Daňa
jdana@mail.muni.cz

Francesco Caputo
fcaputo@unisa.it

Jaroslav Ráček
racek@mail.muni.cz

[1] Department of Computer Systems and Communication, Faculty of Informatics, Masaryk University, Botanická 68a, Brno, Czechia

[2] Department of Pharmacy, University of Salerno, Via Giovanni Paolo II, 132, Fisciano, Italy

Published online: 22 June 2018

market. Since the 1970s, the ability to transfer information and knowledge has grown to be perceived as a crucial source of competitive advantage for companies in achieving success (Arrow 1974). As a consequence, knowledge management (and related topics) has been a subject of intensive scholarly interest focused on organizational learning as a cognitive process or as a function of behavioral change, adapting vision, goals, or decision rules of a company (Borgatti and Cross 2003; Caputo 2016; Del Guidice et al. 2016).

During the last 40 years, multiple shifts of interest in knowledge management happened related to what is to be managed, controlled, or designed. Each of these shifts was connected to new challenges, perspectives, theories, and tools, whose purpose was to support and increase growth and performance of companies. Each of these shifts brought another layer of complexity into the organizational analysis, and also increased the scope of the analysis itself—from individual tasks through cooperation between people to organizations as a whole. Current computational performance and analytical tools allow us not only to analyze interaction within whole companies but also among networks of cooperating companies or online communities (virtual organizations) consisting of hundreds or thousands of people (Zanetti et al. 2012). Interaction between people creates structure and patterns. Understanding these patterns can be used for acquiring deeper insight about the nature of the cooperation, with possible implications for knowledge management and organizational intelligence, which is the aim of the current work. At the same time, organizations with hundreds of employees produce thousands of interactions every day. It is above the human cognitive capacity to fully conceive such amount of information, and, on the top of that, it is conceptually impossible to properly understand patterns of interaction without global perspective. While some patterns are obvious and part of a "common sense," other patterns can be well hidden in the social fabric, yet important, valuable, and quite surprising—once revealed. We need to use a tool to obtain unbiased understanding of interaction patterns in an organization. The complex networks analysis is a suitable tool that allows to achieve such goal.

Best to our knowledge, the current literature applying complex networks analysis (or, interchangeably, social network analysis) in knowledge management lacks a work that would provide a summarization or an overview of existing findings. Moreover, past studies are often descriptive in nature, finding relationships between phenomena. When it comes to practical implications, i.e., how can we make use of these findings to improve knowledge flow in an organization, it is usually up to a reader to deduce. In this paper, we have decided to address these two issues by (a) summarizing existing literature and (b) formulating specific suggestions that may improve knowledge flow in an organization. We have formulated these suggestions by reviewing results and discussions of existing literature, combined with our domain knowledge and experience.

The paper is organized as follows: the "Historical Overview" section provides brief summary of historic evolution of main topic related to knowledge management up to present day. The "Towards Network Analysis for Intelligent Organizations" section introduces the network approach as a conceptual framework. The "Complex Network Analysis" section presents basic principles of collection and analysis of complex network data. The "Suggestions for Knowledge Management" section is aimed on concrete applications of network analysis for knowledge management and organizational intelligence. The paper concludes with the "Conclusion" section where future directions of research are also discussed.

Historical Overview

At the beginning of the last century, knowledge management was focused mainly on controlling the performance of tasks, managing motivation, and the actions of people. The second half of the last century has brought an important change from individual tasks to whole inter-related system of roles, i.e., to relationships between people. In the 1980s, another two major shifts of focus happened—the rise in importance of culture (the system of values and beliefs) and emergence of concept of learning organizations (Stacey 2001). Then, in the 1990s, companies' innovativeness was perceived to replace traditional values like efficiency and quality of production when pursuing market success. Huge body of literature has emerged, identifying "best practices" related to both diffusion and implementation of innovation within firms. The importance of topics related to learning organization and innovation can be illustrated by the popularity of classical work of Nonaka and Takeuchi (1995)—the knowledge creating company that is significantly influenced by systems thinking and complexity theories. Based on this approach, a knowledge-based theory of firm was elaborated, proposing that the capacity of a company to acquire information and create knowledge is the essence of being competitive on the market (Tang 2011).

Another major topic emerging in the 1990s literature was the importance of networking when interaction between individuals raise the awareness of new technologies, solutions, or processes that might be relevant and potentially implemented in own organizations (Swan et al. 1999; Carayannis et al. 2017). As soon as the importance of networking was recognized, the social network analysis started to be used in management science as an exact tool how to get deeper insight about structure of interaction patterns between individuals either within one organization or between multiple companies. This trend has been increasingly apparent especially at the end of millennium, when pioneer works related to beginning of modern network science were published, e.g., the study revealing "the small world effect" (Watts and Strogatz 1998) or preferential attachment in complex networks (Barabási and Réka 1999).

Throughout the history, the notion of knowledge, what it is and how it needs to be treated for the benefit of a company, has changed multiple times. However, a trend is observable: from a knowledge perceived as a "thing" that can be stored towards a knowledge that is more like a process that has to be nurtured (Stacey 2001). The "knowledge-as-process" perspective provides some novel and important insights about how the knowledge is created through interaction of people, on the other hand, it is in contradiction with classical knowledge management practice because process cannot be stored. The dichotomy between knowledge as a thing and knowledge as a process was proposedly resolved by Snowden (2002) who postulates that knowledge is both a process and a thing at the same time and that we need to pay attention to both of these aspects when we manage knowledge flow in an organization.

Although the ability of an organization to learn, adapt, and manage knowledge has been subject of scholarly interest for decades, it is still an open problem even nowadays. With evolution of our society and technological advancements, we are experiencing speeding up in the pace of our lives as information is more available than before (Wajcman 2008; Di Nauta et al. 2015). In economy, such speeding up of life is reflected by the notion of market turbulence, i.e., fast changing and competitive environment on the market, where it is hard to predict customers' demands and preferences. In such environment, firms must seek novel ways on how to foster innovativeness (Ming-Chao and Yun-Zhong 2016; Tronvoll et al. 2017). This radical social and economic evolution relates to new rules and balances in relationships between people and companies and it is based on the shift from the "old" industrial economy to the "new" cognitive economy (Ogiela 2014; Barile et al. 2015).

On the other hand, technological advancements together with availability of information and data may also be a source of opportunity. Data are getting ubiquitous and cheap; therefore, the ability to analyze them and use the outcomes for support of making effective business decisions is an increasingly important set of skills (Chen et al. 2012). Based on a report by McKinsey Global Institute, data analysis is the future source of innovation and competitive advantage on the market. It is expected that experts on data analysis as well as management able to implement data-driven strategies will be in significant shortage in the next few years (Manyika et al. 2011).

Towards Network Analysis for Intelligent Organizations

One possible approach combining data and people for advantage of a company is called organizational intelligence. Based on the perspective of Ercetin et al. (2013), organizational intelligence is a cognitive capacity to combine both human and information systems, where common properties include speed of action and reaction, ability to adapt to changing conditions, flexibility in operation, sensitivity and forecasting, open ideas, and the ability of self-renewal. From the abstract point of view, all these properties are based on the ability of the organization to adequately respond to external and internal environment, reflecting upon top-down feedback loops (decision-making processes and their impact on reality) and bottom-up feedback loops (collecting meaningful information from everyday operation, analyzing them, and implementing the outputs) in order to make relevant decisions while adapting to changing conditions (Daňa 2016).

As Barile et al. (2016) point out, it is time to move the attention from individual employees, dyadic relationships, or groups as basic units of analysis and focus on networks and ecosystems. Not only does the shift towards network thinking reflect current technological and scientific advancements, network approach is by its nature very close to knowledge management as both deal with the concept of interactivity (Calabrese et al. 2017). Knowledge has been traditionally perceived as inherently interactive in nature. In order to "create" knowledge, previously separate pieces of information have to be put together. Without interaction, i.e., without a flow of information, there will be no meaning (Stacey 2001). Individual letters do not produce meaning if they are not put together to compose a word. This interactive nature does not apply only for information. On an abstract level, without a flow of energy, there would be no movement or chemical reactions, no electric appliances would work, economies would be stagnant, and basically everything that we perceive as moving or living could not exist. Life at its essence is based on flow of energy from field with higher concentration of energy to field where the concentration of energy is lower (Goerner 1994).

Applying this analogy back to the knowledge management, we see that to create flow of information, we need to have people with different levels of knowledge and make them interact. Almost every company working with high added value needs to implement methods and tools that would increase the knowledge flow among employees. von Hippel (1988) argues that network with superior knowledge transfer is able to be more innovative than networks with less effective knowledge sharing routines. Therefore, understanding the structure of knowledge sharing patterns and dynamic processes happening in the network could significantly contribute to data-driven managerial decision-making. However, given that mid-sized company can have hundreds of employees, it is almost impossible to correctly understand the nature of these interaction patterns by mere insight or expert judgment. A solution to this problem can be provided by complex network analysis.

Complex Network Analysis

Complex network analysis is used as a quantitative method mathematically grounded in graph theory that is used for analyzing and visualizing of complex systems. Complex system is a set of nontrivial number of agents that are interacting in a common environment such that the system as a whole possesses novel qualities or attributes that cannot be observed at the level of individual agent—the whole is greater than the sum of its parts. Additionally, complex system is able to adapt to changing conditions and reorganize itself, namely its communication, feedback, and workflow patterns (Guastello and Gregson 2011). A swarm of social insects (ants, bees) is a common example of a complex system, where the swarm exhibits intelligent behavior while cognitive capacity of individual insect is negligible. It is the interaction between insects that is creating a meaning—the same principle that applies to knowledge creation in organizations. Basically, any complex system can be perceived as a network. And, as Barabási (2016) points out, we cannot understand complex systems unless we develop a deep understanding of the networks behind them.

Traditionally, the links between people are perceived as channels through which the flow of resources (information, knowledge, or material) is facilitated or constrained (Tröster et al. 2014). Repeated interaction between nodes is the source of overall network patterns and structure, and, consequently, also a base for all measures, metrics, and visualization of the network.

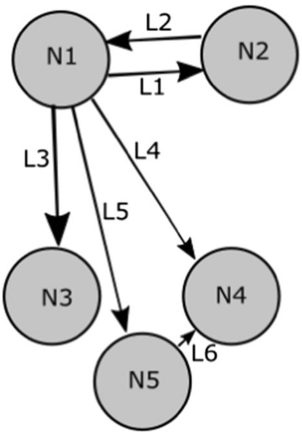
Data Collection

To start analyzing interactions in an organization through network theory, we need to collect basic building blocks of the network—the interaction between two employees, the dyadic relationship. Employees are represented as nodes, and interactions between them are represented as links. In the working environment, we usually consider the interactions to be directed, i.e., they have a sender and receiver. For instance, when person *N1* sends an email to person *N2*, a link $N1 \rightarrow N2$ is created. If person *N2* would reply to sender *N1*, then a separate link $N2 \rightarrow N1$ would be created. Storing information about interactions into a table is a first step in network analysis, as illustrated in Fig. 1 below.

The sources of employees' interaction data can include the following: face-to-face communication, emails, instant messaging, voice calls, response to requests, assigning tasks, interactions in workflow systems, participation on meetings, participation in online work-related discussions, commenting documents, etc. It is usually up to researchers' decision which sources to include or combine to construct cooperation network, based on availability and representativeness of data.

For research design with well-defined time frame and smaller scope (e.g., analyzing interaction of team members during weekend teambuilding event), we may want to collect data about face-to-face communication. It is uneasy to track down direct personal interaction that is not transferred through an electronic medium. There is a commercial solution that allows to collect such data with devices called sociometric badges (Olguín Olguín and Pentland 2007), which the participants of an experiment wear around their necks. The data can be exported and analyzed by any available third party tool or with dedicated software supplied with badges. Recently, an initiative for releasing an open source version of sociometric badges has emerged (Lederman et al. 2017).

As mentioned above, our aim in the data collection phase is to acquire sender and recipient data in the form of a table. In case that we would like to analyze interactions between employees from the whole organization, we would probably use the communication channel that is commonly used by majority of people—a collaborative environment, internal email system, internal instant messaging, if applicable. Subsequently, we need to use scripts to process the interactions metadata that extract sender and recipient information. A table with list of interactions between people is a format that can be used as an input for most of the commonly available tools for network analysis. For advanced analysis, a time stamp of each link creation can be used as additional variable in the table to study temporal progress of the network. See Holme and



ID	Sender	Recipient
L1	N1	N2
L2	N2	N1
L3	N1	N3
L4	N1	N4
L5	N1	N5
L6	N5	N4

Fig. 1 Storing interaction data in a table. Left-hand side of the figure represents a series of interactions (e.g., email messages), denoted as links (L1…L6), between a group of employees (N1…N5). Right-hand side of the figure illustrates representation of such interaction in a table. The numbering sequence L1…L6 is random. If a time stamp of each interaction is available, the flow of time can be used as a numbering sequence. In that case, there will be additional column in the table denoting the time when the email was sent

Saramäki (2013) for an introduction to temporal networks analysis. An ID of a team, department or a project can be used as another variable in the table, to analyze structural properties of the cooperation network.

Collecting network data from collaborative environment or messaging system is not the only way how to acquire the data. It is possible to use questionnaires or other indirect methods to receive information about connections between employees. In this case, we ask respondents to write down a list of the colleagues that they frequently cooperate with, and estimate how often do they communicate with them, what is their attitude towards them, who do they ask for help when they encounter a work-related issue, who is the source of important information, etc. The responses would then be used as attributes of the link between two employees, and would allow to construct "advice" networks, "friendship" networks, or even "hinderance" network (of colleagues whose social influence obstructs one's ability to perform well).

Reader interested in the details about preparation of network data can be referred to Borgatti et al. (2013).

Tools for Network Analysis

Once the data are collected and a table with all the nodes and attributes we want to include in the analysis is prepared, we may proceed to data processing and import the table into the analytic tool. There is a variety of tools available to choose from: some of them were developed specially for analyzing complex networks and are free to use, e.g., Gephi, NetworkX, Pajek, or graphviz; some are licensed but offer complex functionality, including processing the data, testing hypotheses, etc., e.g., UCINET; and also, general purpose analytic tools can be used for analyzing network data with use of specific libraries, e.g., R or Processing. Choice of a particular tool can be based on preference for certain environment, programming language, learning curve of the tool, analytic capabilities, esthetic properties of the visualization, etc. Despite the differences in user interface and functionality, all the above-mentioned tools can be used for calculating network properties.

Node-Centric Measures

Not all nodes in a network are of same importance. Some of them are more central, connected to many other (important) nodes, some nodes are peripheral, having direct access only to its close neighborhood. In order to analyze the importance of individual nodes, analytic tools perform specific algorithms that calculate the measures called network centralities (Barabási 2016).

There are numerous centrality measures that capture various attributes of nodes to highlight their specific importance in a studied network. For purposes of this paper, we only mention a few of them that are most commonly known and often found to be important when knowledge diffusion in organization is focused. An interested reader can refer to any of the handbooks that introduce network theory and social network analysis, e.g., Wasserman and Faust (1994), Newman (2010), Barabási (2016), among others.

Frequently used measure of importance or popularity of a node in a network is the degree centrality (denoted as δ)δ(v), referring to the number of neighbors directly connected that the node being observed. In directed networks, we may distinguish the in-degree measure (to what extent plays the node role of a communication target) and out-degree measure (how important is the node as initiator or source of communication). While some nodes may have balanced in- and out-degree measures, some nodes may have significantly higher in-degree to out-degree (and vice versa) which might be interesting information especially if such node occupies certain position in an organizational structure (e.g., team leader, manager, etc.). The degree centrality measure is illustrated in Fig. 2.

Another frequently used node-centric centrality measure is betweenness centrality which was formally defined by Freeman (1977). The importance of a node is inferred from the fact whether it lies on many shortest paths connecting two other nodes, i.e., it acts as a "bridge" between otherwise sparsely connected parts of a network. If we would remove such node from a network, the cost of communication of other connected nodes would rise because they would have to follow other, longer paths. Betweenness centrality $C_B(u)$ of node u can be formally defined as

$$C_B(u) = \sum_{x \neq y} \frac{|S(x,u,y)|}{|S(x,y)|}$$

where $S(x,y)$ is the set of shortest paths between two nodes x, $y \in V(G)$ and $S(x,u,y) \subseteq S(x,y)$ is the set of the shortest paths passing through node $u \in V(G)$. We assume that all nodes can be reached and that all shortest paths between two nodes have non-zero value. Illustration of node's betweenness centrality measure can be seen on Fig. 3.

One of the most prominent measures related to high social and cognitive capital is the concept of structural hole. To explain this concept, let us consider a fictive example of a company where people communicate only with colleagues from the same department. The more they communicate with each other, the higher is the

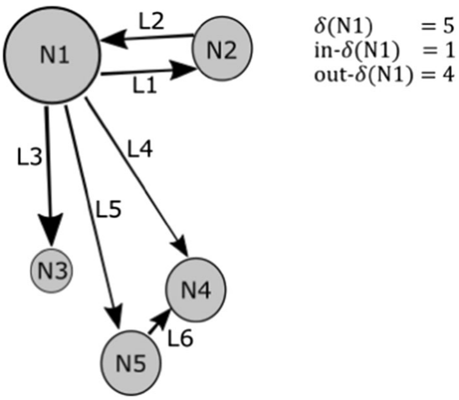


Fig. 2 Degree centrality measure. Diameter of the node increases with degree centrality. The total degree centrality of the node N1 is 5, as there is a total of five links connecting N1 with other nodes, from which one is directed towards N1, and four are outcoming of N1, referring to in- and out-degree centrality, respectively

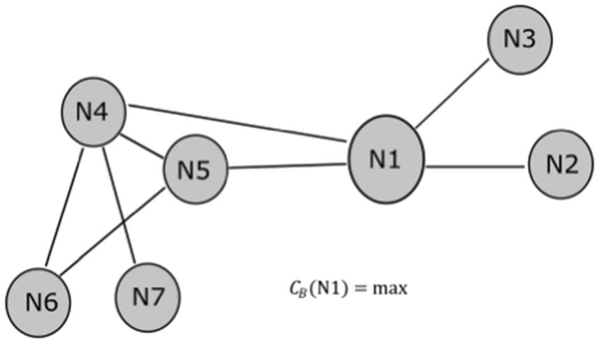


Fig. 3 Betweenness centrality measure. The node N1 has the greatest value of C_B as it lies on highest number of shortest paths between any other two nodes from the example network

probability that they have access to same information; therefore, unique information is rare. The communication barriers between departments represent the structural hole—any person that would span two separate departments would get into favorable position as information from one department might be valuable (and otherwise inaccessible) for the other department, and vice versa. To measure this phenomenon, the author of the structural hole concept, Ronald Burt (2009), suggests calculating the network constraint measure which represents a lack of access to structural hole. The network constraint c_{ij} of relation between i and j can be formally written down as

$$c_{ij} = \left(p_{ij} + \sum p_{iq} p_{jq}\right)^2, q \neq i, j$$

where p_{ij} is the strength of direct links from i to j, and $\sum p_{iq} p_{jq}$ is the sum of indirect link strength from i to j via all q. The strength of a link can be seen as a proportion of invested resources (e.g., time)—the more time one person spends communicating with a colleague, the stronger is the link between them. Then, the measure of structural hole $Sh(j)$ of a node j can be described as

$$\mathrm{Sh}\ (\mathrm{j}) = 1 - \sum_j \left(p_{ij} + \sum p_{iq} p_{jq}\right)^2, q \neq i, j$$

and illustrated in Fig. 4 below.

Network-Centric Measures

Apart from node-centric measures that are focused on importance of individual nodes, there is another group of algorithms used for calculations related to multiple nodes or the network as a whole—its size, diameter, density, or structure, e.g., clustering coefficient, average degree, average shortest path, or the distribution of nodes' attributes. These measures are used as statistical

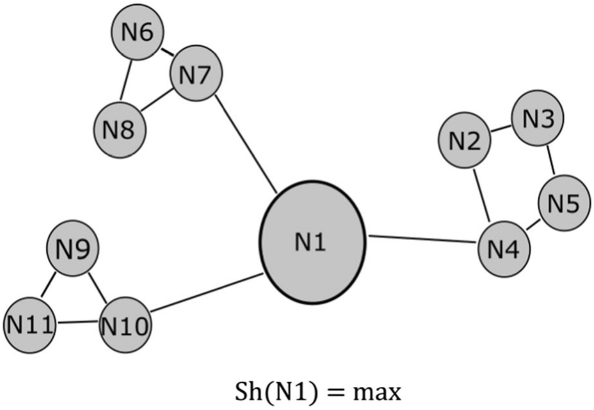


Fig. 4 Structural hole measure. The node N1 has the greatest value of Sh(j) as it connects three otherwise disconnected parts of the network, resulting in a high social capital

descriptions of macroscopic network properties which can be useful when comparing different data samples, for example. Existing literature related to the topic of this paper usually focuses on node-centric measures because, in the organizational setting, the goal is to detect individuals occupying favorable network positions and analyze the circumstances of such observation. On the other hand, it might be useful to analyze how people form groups through communication. In particular, we can compare formal and informal organizational structure to obtain insight whether company hierarchy is consistent with the way how employees tend to interact naturally. Identification of groups in social network is commonly addressed as community detection, and it is receiving a lot of scholarly interest (Leskovec et al. 2010), including the detection of overlapping communities (Xie et al. 2013). There are many

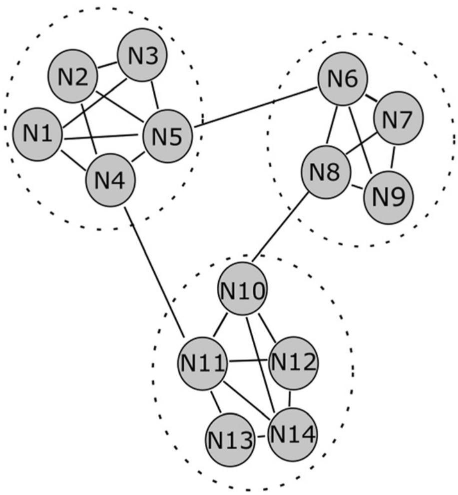


Fig. 5 Community structure. Community refers to a group of nodes that are densely connected insight the community but sparsely connected between groups

approaches that use different algorithms for community detection in networks, interested reader can be referred to Papadopoulos et al. (2012), for instance. An example of community structure is illustrated in Fig. 5.

Network Visualization

When collecting data for network analysis in a company, we might acquire a sample with hundreds of nodes and thousands of links. To better orientate in such an amount of data, most network analytic tools use visualization. The visualization is a way of obtaining a general overview about the structure of the network and improving perceptual abilities of the observer for finding important information in the data. The goal of visualization algorithms is not only to provide accurate data but also to do it in a visually appealing way (Bastian et al. 2009). For example, the layout algorithm used in Gephi is continuously calculating the attractive and repulsive forces between individual nodes in order to display the network that is accordingly reflecting relationships between nodes (Jacomy et al. 2014).

An example of how a visualization of a sample network in Gephi tool may look like is portrayed in Fig. 6 below.

The network visualization is showing some of its important properties at a glance: identity of its most central nodes, existence of communities, overall structure, and mutual distance between various parts of the network (communities, teams, organizational units, separate parts loosely connected with the rest of the network, etc.). An example, how one can be data sample visualized in multiple ways to highlight different network properties, is illustrated in Fig. 7.

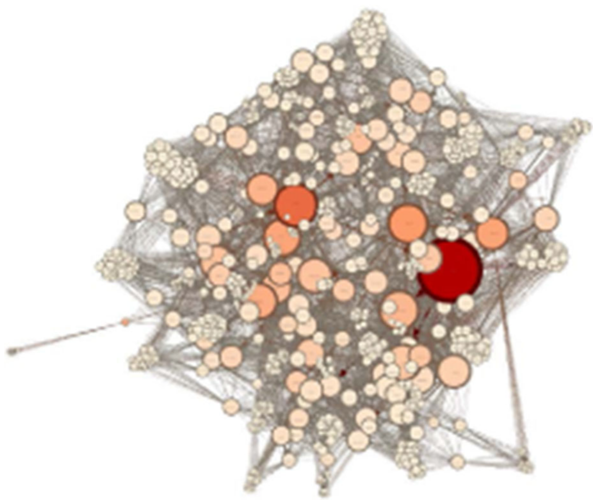


Fig. 6 Example of network visualization. Size of a node refers to its degree centrality (greater diameter = higher degree) and hue of red color refers to betweenness centrality (darker red = higher betweenness). The ForceAtlas2 algorithm for layout automatically positions highly central nodes in the core of the network, detects communities, separates parts of the network, etc.

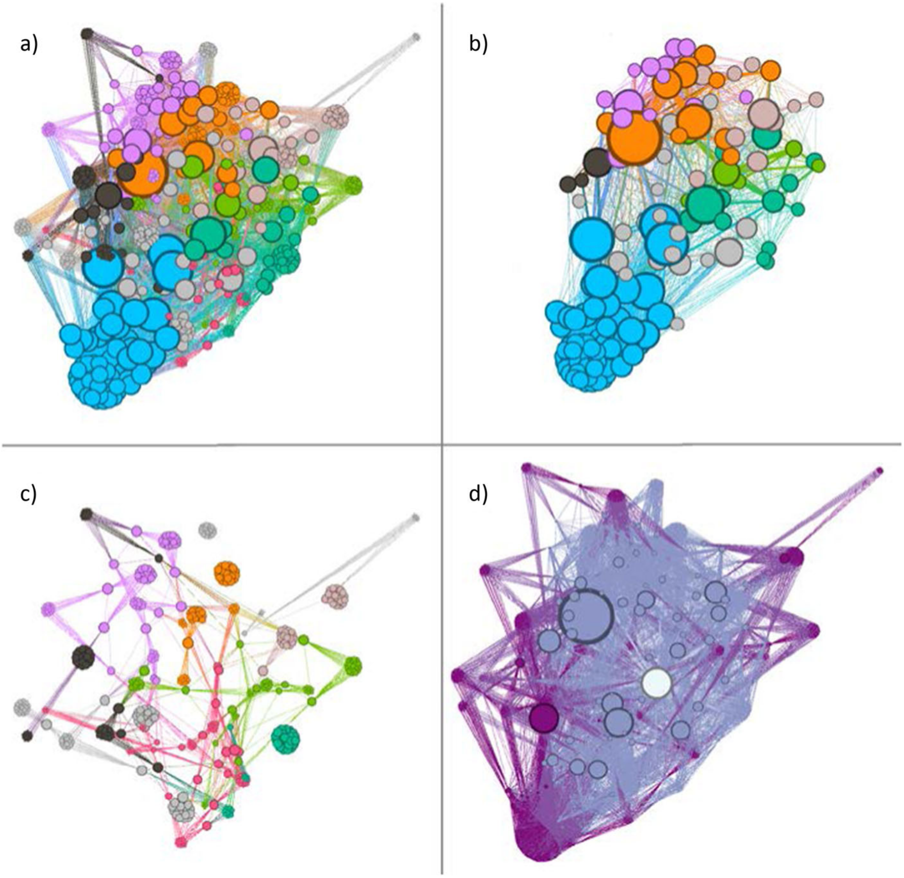


Fig. 7 Multiple visualizations of a single data set. In panel (**a**), the diameter of a node refers to its degree centrality (greater diameter refers to higher value of degree centrality), while color indicates node's membership in a particular cluster. Panel (**b**) represents a subset of the nodes depicted in panel (**a**) from which peripheral nodes (with low degree centrality) were removed. On the other hand, panel (**c**) visualizes these peripheral nodes which were filtered out from the original network from panel (**a**). Finally, panel (**d**) portrays two path-based network measures. Diameter of a node proportionally illustrates its betweenness centrality value and hue of purple color indicates eccentricity measure—dark purple nodes are highly eccentric while white node in the middle of the network is least eccentric (i.e., on average, it can be reached by lowest number of connections from any other node)

Visualization combined with accurate calculations of network properties can be a source of deeper insight about interaction structure of a company and used as a support for managerial decision-making processes.

Network Analysis Summarization

Network analysis is a complex task with its own methodology whose detailed description is above the scope of this work. There are numerous books covering this topic in a comprehensive way so that the reader will be guided through the analysis from the beginning to the end, e.g., Scott (2000), Prell (2011), Borgatti et al. (2013), or Robins

(2015). To provide just a brief overview of the steps taken in the analysis, Table 1 below summarizes this chapter.

Suggestions for Knowledge Management

Companies are living organizations, full of interaction between employees, departments, customers, partners, or external parties. Cooperation and coordination of the work is more efficient and transparent with the use of collaborative environments and electronic communication. While minding the personal privacy issue, we can use the available metadata about these interactions for enhancing the knowledge flow in an organization. The following section is presenting research aimed on application of network analysis in organizations with implications for knowledge management and organizational intelligence. These suggestions represent logical implications from results of previous research combined with our domain knowledge and experience.

Network Centrality and Performance

Position of a node in a network is significantly affecting the flow of resources that goes through this node. Employees with a lot of social ties, i.e., with high degree centrality, usually have significantly high knowledge capital, as they have better access to various parts of the network that may possess unique information compared to other parts of the network (Chang-ling et al. 2009; Goldenberg et al. 2009). It is common that employees with high degree centrality already occupy high positions in company hierarchy. However, exceptions from this rule might be surprising as, e.g., a postman or maintenance staff might have high measures of degree centrality within the company network. Based on this, we can formulate the following suggestions:

Table 1 Summarization of the analysis

Step in the analysis	Description
1. Research design	Decision related to purpose and scope of the research, type of data to be collected (electronic communication, questionnaires, sociometric badges, other)
2. Data collection	Conducting an experiment, survey collection or data mining
3. Data preparation	Creating a table with source and target ID and attributes to be included in the analysis
4. Data analysis	Importing the table into one of available tools, application of algorithms for calculation of node centralities, community detection, network layout and visualization, application of color and size effects
5. Results	Overview of the network layout, identification of communities and separated parts of the network, inspection of highly central nodes
6. Application	Using the obtained results to aim the suggestions for knowledge management at appropriate nodes and parts of the network

S_1: Targeting employees with high degree centrality is the most efficient strategy for diffusion of novel knowledge, practices, or visions through a company.

S_2: It is advisable to include employees with high degree centrality into the process of disseminating or collecting information related to everyday operation even though they are not highly ranked in official organizational hierarchy.

According to Tsai (2001), highly central organizational units (in terms of degree centrality) correlate with better performance and innovativeness if, at the same time, they are also able to absorb the novel knowledge they have access to. In other words, being central can result in higher performance only if the particular node or community is able to learn and process different sources of information and transform it into a knowledge. Tang (2011) is extending this notion by postulating that it is also important to efficiently and comprehensively disseminate processed knowledge which might be related to social intelligence and verbalization skills.

It is important to note that people are not always willing to share the information they collected. According to Gilmour (2003), this issue can be resolved by creating an environment where people would naturally want to exchange knowledge: when they seek a common goal or when they are finding a solution for a similar problem. Having a common goal and comparable level of prior knowledge also increases absorptive capacity because discussing the same or related problem from multiple perspectives may benefit all participants. At IBM, an integrated collaborative environment allows to seek colleagues by their expertise or the whole community that is working on a specific issue. Additional features like bookmarking resourceful websites or documents for problem solving is also based social network analysis (Lin et al. 2009). An importance of shared goals for increased cognitive capital transfer is also highlighted by Chow and Chan (2008) or Inkpen and Tsang (2005). As a summary, the suggestion could be formulated as follows:

S_3: Adopting a method allowing to connect employees with similar challenges may increase knowledge flow. This effect is increased with highly central employees.

Connecting Communities

Group of people sharing same social or spatial environment tend to create communities that are densely connected inside and sparsely connected to other parts of the network. As the members of a community have access to very similar everyday experience and information, there is a low probability of unique knowledge flow within the community (Singh 2005). Additionally, information travels fast within a community but has difficulty to reach other communities (Barabási 2016). Inside a community, a certain problem or concept can be very well apprehended as every community member has similar experience and understanding of it, but flow of knowledge is low because low amount of novel information is transferred between community members. On the other hand, this knowledge possessed by the community might be unique and highly valuable to other communities and parts of the company network, resulting in an increase of the knowledge flow.

Therefore,

S_4: To increase the overall value of the knowledge, it might be useful to target specific communities and support both formal and informal communication channels between them and other parts of the network.

However, the question whether it is desirable and beneficial to support communication with a specific community and the rest of the network is up to a managerial decision, depending on what is the target department and if the increased communication will actually bring in the value.

Overlapping Structural Holes

Structural hole can be described as an area without connections between two adjacent, internally highly connected communities. A person that can connect across these two cohesive groups can benefit from unique knowledge of both communities, increasing their social and knowledge capital (Ahuja 2000; Burt 2004). Analyzing interaction network within an organization might be useful because often times the communication related to knowledge, products, processes, or technologies is suboptimal or not applied for maximum advantage (Hoffman et al. 2005).

Connecting two disconnected cohesive groups is also called structural folding and it has been found to be related to innovative potential (Vedres and Stark 2010). This relationship was further investigated by De Vaan et al. (2015) who came to a conclusion that this phenomenon is related to innovative success and good performance only if it is bringing cognitively distant groups into contact. A process of overlapping a structural hole (Fig. 8a) into a structural folding (Fig. 8b) between two cognitively distant communities is illustrated below.

It is not the overlapping structure of the network itself, but the different concentration of knowledge and cognitive setting between the groups what is the source of performance and innovation. This is in accordance with theoretical presumption presented in the "Towards Network Analysis for Intelligent Organizations" section that knowledge flow is created between fields with different concentration of information (Goerner 1994).

S_5: Innovative potential can be fostered by identifying and bridging structural holes within an organizational network if it would connect cognitively distant groups.

Company as a Small World

One of prominent measures related to the analysis of a whole network is the average path length. This measure is describing how long is a shortest path all pairs of nodes in the network or, in other words, how many intermediary steps are between them. In sparsely connected networks, the average path is longer than in dense networks because

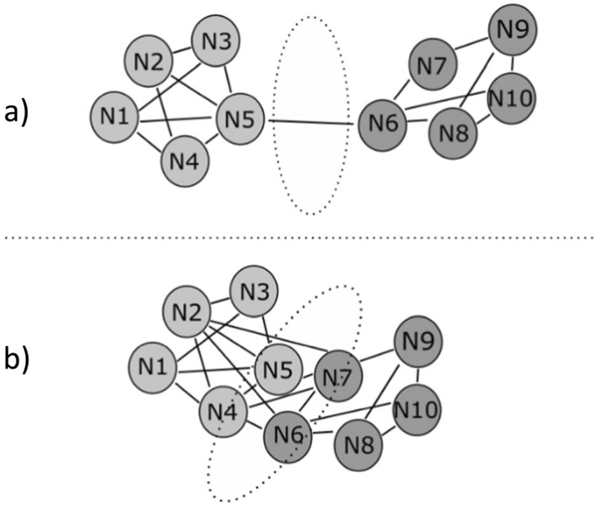


Fig. 8 Structural hole (**a**) becoming structural fold (**b**)

the information often has to take longer "detours" between two otherwise not that distant but disconnected nodes. Within an organization, longer average path implies higher costs for knowledge management because the longer a piece of information travels, the more it is distorted and less reliable (Li et al. 2009). The easier the transfer, the less time and effort is required and the more likely it is that the transfer will be successful (Reagans and McEvily 2003).

Setting up an organizational culture in a way that communication is easy both horizontally and vertically on the company hierarchy is a good way how to shorten average path length and creating "small world" where everyone is connected to everyone else by just a few intermediary steps (Watts and Strogatz 1998). Moreover, informal relationships between employees may also have beneficial effects for knowledge transfer, as they might be more willing to share their experience and best practices in a friendly setting (Yang and Tang 2004). Allen et al. (2007) argue that it is better to set up an environment allowing for developing informal relationship among employees organically rather than designing this in a top-down manner, while Li et al. (2009) recommend that developing informal relationships should be to some extent supported by reasonable technical means and strategic management.

> S_6: Setting up supportive environment for developing both formal and informal relationships across all levels of company hierarchy may help creating "small world" network, reducing costs for knowledge management and increasing knowledge transfer.

Monitoring Stress of Highly Central Employees

Skills, knowledge, and experience of employees are qualities that are not equally distributed within an organization. Certain employees may possess unique capabilities that allow them to perform very well at specialized tasks, e.g., coordinating cooperation of many other employees, that significantly contribute to overall performance of an organization and it would be very hard to substitute them in case of their departure from the company. According to Tröster et al. (2014), highly centralized networks might be highly efficient in terms of distributing information but they are also at risk of overburdening of the central individuals.

A case study illustrating a situation when highly valuable and highly central contributor leaves a project is presented by Zanetti et al. (2013). The authors describe that an arrival of a single person into the project has significantly increased the performance of the whole collaboration network. Eventually, due to long-term overburden and personal dissatisfaction, this particular contributor eventually left the project, causing a serious drop of overall performance of the network, although their task was mainly focused on coordination of work of others. After this person left, the network was performing even worse than it was before their arrival into the project.

It is not unusual that a single employee may have such important impact on performance of the whole organization. Highly central employees are often those who are also high performers (Ehrlich and Cataldo 2012). Ernst et al. (2000) report that top performing R&D employees are many times more valuable compared to low-performers. High level of their performance is also interconnected with high level of knowledge capital. Losing a top performing employee is not only a loss of valued human resource but also a significant disruption of knowledge transferring network. Based on these arguments, it is advisable to prevent an onset of central employees' dissatisfaction:

S_7: Monitoring stress levels of highly central employees could be used as a warning signal for their possible dissatisfaction in the future.

In order to lower the overburden and possible dissatisfaction, it is important to implement means of appreciation, rewarding, and motivating of the key employees. For more detailed information, related to preventing overburden of highly central and highly performing individuals, readers can be referred to Oldroyd and Morris (2012).

Conclusion

In this article, we present multiple approaches utilizing the complex network analysis in organization aimed on inspection of processes related to knowledge management. Based on that, we attempted to formulate suggestions that might be used as a support for managerial decisions and strategy making that would foster knowledge flow, innovativeness, and performance of a company. Innovativeness and performance of employees are based on quality of their interaction; therefore, complex network analysis is a highly suitable tool as it provides methods for inspecting the nature of interacting systems.

Analyzing complex networks can provide understanding and insights about qualities and interaction patterns of cooperating employees that would be otherwise very hard to obtain. On the other hand, it is a quantitative method, reflecting upon certain aspects of reality and discarding others. Application of proposed suggestions has to be combined with respect to particular company and people that is the network representing. It is advisable to combine insights from network analysis with other quantitative or qualitative methods and expert decisions in order to achieve desired results.

Throughout the text, it was suggested that connecting different parts of network should increase the knowledge flow. On the other hand, supporting the creation of new connections must make sense—it should link people or teams that would benefit from that contact. The architecture of connections matters therefore creating random or collective connections might not end up in the desired outcome (Cowan and Jonard 2004). This argument also supports the need for sensitive combination of network analysis, suitable qualitative methods, and qualified decisions.

Complex network analysis is a powerful tool that has the potential to help organizations grow. At the same time, it has to be applied appropriately in order to be useful. We believe that interdisciplinary cooperation between management studies, organizational studies, and computer/data science might be fruitful when developing this research endeavor. Future direction of this cooperation could address validation of individual suggestions, developing an environment that would allow to analyze different type of data, designing algorithms that would predict certain behavior based on specific network patterns, examining contexts in which change of network structure results in desired outcome, or inspecting psychological and cultural aspects that modify the influence of network phenomena on the knowledge flow.

References

Ahuja, G. (2000). Collaboration networks, structural holes, and innovation: a longitudinal study. *Administrative Science Quarterly, 45*(3), 425–455.

Allen, J., James, A. D., & Gamlen, P. (2007). Formal versus informal knowledge networks in R&D: a case study using social network analysis. *R&D Management, 37*(3), 179–196.

Arrow, K. J. (1974). *The limits of organizations*. New York: W. W. Norton.

Barabási, A.-L. (2016). Network Science. Cambridge: Cambridge University Press.

Barabási, L.-A., & Réka, A. (1999). Emergence of scaling in random networks. *Nature, 286*(5439), 509–512.

Barile, S., Saviano, M., & Caputo, F. (2015). How are markets changing? The emergence of consumers market systems. In G. Dominici, The 3rd International Symposium Advances in Business Management. "*Towards Systemic Approach*". Avellino: Business Systems E-book Series.

Barile, S., Lusch, R., Reynoso, J., Saviano, M., & Spohrer, J. (2016). Systems, networks, and ecosystems in service research. 27(4), 652–674.

Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: an open source software for exploring and manipulating networks. Proceedings of the Third International ICWSM Conference.

Borgatti, S., & Cross, R. (2003). A relational view of information seeking and learning in social networks. 49 (4), 432–445.

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing social networks*. London: SAGE Publications.

Burt, R. S. (2004). Structural holes and good ideas. *American Journal of Sociology, 110*(2), 349–399.

Burt, R. S. (2009). *Structural holes: the social structure of competition*. Harvard: Harvard University Press.

Calabrese, M., Iandolo, F., Caputo, F., & Sarno, D. (2017). From mechanical to cognitive view: the changes of decision making in business environment. In *Social Dynamics in a System Perspective*. New York: Springer.

Caputo, F. (2016). A focus on company-stakegolder relationships in the light of the stakeholder engagement framework. In *Innovation, Entrepreneurship and Digital Ecosystems* (pp. 455–470). Cyprus: EuroMed Press.

Carayannis, E., Caputo, F., & Del Giudice, M. (2017). Technology transfer as driver of smart growth: a quadruple/quintuple innovation framework approach. In *Global and national business theories and practice: bridging the past with the future* (pp. 295–315). Cyprus: EuroMed Press.

Chang-ling, L., Xue-mei, J., & Hai-yun, X. (2009). Optimize knowledge networks to improve enterprises' knowledge management performance based on complex networks theory. *International Conference on Computational Intelligence and Software Engineering*.

Chen, H., Chlang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: from big data to big impact. *MIS Quarterly, 36*(4), 1165–1188.

Chow, W. S., & Chan, L. S. (2008). Social network, social trust and shared goals in organizational knowledge sharing. *Information Management, 45*(7), 458–465.

Cowan, R., & Jonard, N. (2004). Network structure and the diffusion of knowledge. *Journal of Economic Dynamics & Control, 28*(8), 1557–1575.

Daňa, J. (2016). Suggestions for knowledge management based on complex network analysis. In F. Caputo, Governing business systems. Theories and challenges for systems thinking in practice. In *Book of Abstracts*. Avellino: Business Systems E-Book Series.

De Vaan, M., Stark, D., & Vedres, B. (2015). Game changer: the topology of creativity. *American Journal of Sociology, 120*(4), 1144–1194.

Del Guidice, M., Caputo, F., & Evangelista, F. (2016). How are decision systems changing? The contribution of social media to the management of decisional liquefaction. *Journal of Decision Systems, 25*(3), 214–226.

Di Nauta, P., Merola, B., Caputo, F., & Evangelista, F. (2015). Reflections on the role of university to face the challenges of knowledge society for the local economic development. *Journal of Knowledge Economy*, 1–19.

Ehrlich, K., & Cataldo, M. (2012). All-for-one and one-for-all?: a multi-level analysis of communication patterns and individual performance in geographically distributed software development. *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*.

Ercetin, S. S., Potas, N., Kisa, N., & Acikalin, S. N. (2013). *To be on the edge of chaos with organizational intelligence and health. In S. Banerjee, Chaos and complexity theory for management*. Hershey: IGI Global.

Ernst, H., Leptien, C., & Vitt, J. (2000). Inventors are not alike: the distribution of patenting output among industrial R&D personnel. *IEEE Transactions on Engineering Management, 47*(2), 184–199.

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry, 40*, 35–41.

Gilmour, D. (2003). How to fix knowledge management. *Harvard Business Review, 81*(10).

Goerner, S. J. (1994). *Chaos and the evolving ecological universe*. Luxembourgh: Gordon and Breach.

Goldenberg, J., Han, S., Lehmann, D. R., & Hong, J. W. (2009). The role of hubs in the adoption process. *Journal of Marketing, 73*, 1–13.

Guastello, S. J., & Gregson, R. A. (2011). *Nonlinear dynamical systems analysis for the behavioral sciences using real data*. Boca Raton: CRC Press.

Hoffman, J. J., Hoelscher, M. L., & Sherif, K. (2005). Social capital, knowledge management, and sustained superior performance. *Journal of Knowledge Management, 9*(3), 93–100.

Holme, P., & Saramäki, J. (2013). *Temporal networks*. Berlin: Springer-Verlag.

Inkpen, A. C., & Tsang, E. W. (2005). Social capital, networks, and knowledge transfer. *The Academy of Management Review, 30*(1), 146–165.

Jacomy, M., Venturini, T., Heymann, S., & Bastian, M. (2014). *ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software*. 9. Medialab center of research 560.

Lederman, O., Calacci, D., MacMullen, A., Fehder, D. C., Murray, F. E., & Pentland, A. S. (2017). Open badges: a low-cost toolkit for measuring team communication and dynamics. *arXiv*.

Leskovec, J., Lang, K. J., & Mahoney, M. (2010). Empirical comparison of algorithms for network community detection. Proceedings of the 19th International Conference on World Wide Web. ACM, pp. 631–640.

Li, C.-l., Ji, X.-m., & Xu, H.-y. (2009). Optimize knowledge networks to improve enterprises' knowledge management performance based on complex networks theory. *International Conference on Computational Intelligence and Software Engineering CiSE 2009*. Wuhan.

Lin, C.-Y., Cano, N., Liu, S. X., Papadimitriou, S., Sun, J., & Yan, X. (2009). SmallBlue: social network analysis for expertise search and collective intellgience. *IEEE* 25th International Conference on Data Engineering (pp. 1483–1486). IEEE.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Hung Byers, A. (2011). *McKinsey&Company*. Retrieved November 12, 2016, from http://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/big-data-the-next-frontier-for-innovation

Ming-Chao, W., & Yun-Zhong, K. (2016). Market Turbulence, Entrepreneurial orientation and explorative innovation: *the role of organizational capabilities*. 5(1).

Newman, M. (2010). Networks: an introduction. In *Oxford University Press*. Oxford.

Nonaka, I., & Takeuchi, H. (1995). The knowledge-creating company: how Japanese companies create the dynamics of innovation. In *Oxford: Oxford Unversity Press*.

Ogiela, L. (2014). Towards cognitive economy. *Soft Computing, 18*(9), 1675–1683.

Oldroyd, J. B., & Morris, S. (2012). A human resource response to social capital's detrimental effect of information overload on star employees. *Academy of Management Review, 37*(3), 396–418.

Olguín Olguín, D., & Pentland, A. (2007). Sociometric badges: state of the art and future applications. *Doctoral colloquium presented at IEEE 11th International Symposium on Wearable Computers*.

Papadopoulos, S., Kompatsiaris, Y., Vakali, A., & Spyridonos, P. (2012). Community detection in social media. *Data Mining and Knowledge Discovery, 24*(3), 515–554.

Prell, C. (2011). *Social network analysis: history, theory and methodology*. London: SAGE.

Reagans, R., & McEvily, B. (2003). Network structure and knowledge transfer: the effects of cohesion and range. *Administrative Science Quarterly, 48*(2), 240–267.

Robins, G. L. (2015). *Doing social network research: network-based research design for social scientist*. London: SAGE.

Scott, J. (2000). *Social network analysis: a handbook*. London: SAGE.

Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science, 51*(5), 756–770.

Snowden, D. (2002). Complex acts of knowing: paradox and descriptive self-awareness. *Journal of Knowledge Management, 6*(2), 100–111.

Stacey, R. D. (2001). *Complex responsive processes in organizations*. Abingdon: Routledge.

Swan, J., Newell, S., Scarbrough, H., & Hislop, D. (1999). Knowledge management and innovation: networks and networking*., 3*(4), 262–275.

Tang, F. (2011). Knowledge transfer in intra-organization networks. *Systems Research and Behavioral Science, 28*(3), 270–282.

Tronvoll, B., Barile, S., & Caputo, F. (2017). A systems approach to understanding the philosophical foundation of marketing studies. In *Social Dynamics in a System Perspective*. New York: Springer.

Tröster, C., Mehra, A., & van Knippenberg, D. (2014). Structuring for team success: the interactive effects of network structure and cultural diversity on team potency and performance. *Organizational Behavior and Human Decision Processes, 124*(2), 245–255.

Tsai, W. (2001). Knowledge transfer in intraorganizational networks: effects of network position and absorptive capacity on business unit innovation and performance. *Academy of Management Journal, 44*(5), 996–1004.

Vedres, B., & Stark, D. (2010). Structural folds: generative disruption in overlapping groups. *American Journal of Sociology, 115*(4), 1150–1190.

von Hippel, E. (1988). *Sources of innovation*. Oxford: Oxford University Press.

Wajcman, J. (2008). Life in the fast lane? Towards a sociology of technology and time. *The British Journal of Sociology, 59*(1), 59–77.

Wasserman, S., & Faust, K. (1994). *Social network analysis: methods and applications (structural analysis in the social sciences)*. Cambridge: Cambridge University Press.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature, 6*(4), 440–442.

Xie, J., Kelley, S., & Szymanski, B. K. (2013). Overlapping community detection in networks: the state-of-the-art and comparative study. *ACM Computing Surveys, 45*(4), 1–35.

Yang, H.-L., & Tang, J.-H. (2004). Team structure and team performance in IS development: a social network perspective. *Information Management, 41*(3), 335–349.

Zanetti, M. S., Sarigöl, E., Scholtes, I., Tessone, C. J., & Schweitzer, F. (2012). *A quantitative study of social organisation in open source software communities*. Retrieved December 2, 2016, from arXiv: http://arxiv.org/abs/1208.4289

Zanetti, M. S., Scholtes, I., Tessone, C. J., & Schweitzer, F. (2013). The rise and fall of a central contributor: dynamics of social organization and performance in the GENTOO community. Retrieved December 4, 2016, from arXiv: http://arxiv.org/abs/1302.7191