REVEALING KNOWLEDGE NETWORKS FROM COMPUTER MEDIATED COMMUNICATION IN ORGANIZATIONS

Abstract

In today's knowledge driven economy, knowledge is considered to be the key factor in defining the success of an organization. We have learned that knowledge is residing in the informal network of the organization. Hence, to improve performance, it is the informal knowledge network that should be examined and developed. For this purpose, social network analysis is increasingly applied in business contexts. This is, however, a new domain, which is still in development. This paper aims to aid in this development by researching how representative knowledge networks can be revealed in organizations. While surveying is a common first option to capture an organizational network, this technique may not always be suitable. Communication sources (e.g. e-mail) may provide an alternative, however, we do not know to what extent these sources can represent the actual knowledge network. This paper examines a Dutch IT services organization. Here, a web-survey among the employees baselines the knowledge network, which is compared to 3 communication networks from the same organization, captured by means of e-mail, telephone and SMS (Short Message Service) communication (also known as text messaging or texting). A comparison is made by means of correlating the network matrices and by comparing essential network properties. Findings show that only the e-mail network is significantly representative for the baselined knowledge network. This exercise is exploratory in nature as only one organization is examined, but comprehensive with regard to the richness of data that is available for examination. From our findings we gain insight in the extent to which networks, captured from e-mail, telephone and SMS archives can represent an organizational knowledge network.

Keywords: Informal network, Learning network, Advice network, Social Network Analysis, Mail analysis

1 INTRODUCTION

Knowledge management is widespread in organizations and involves the management of knowledge processes concerning generating, sharing and using knowledge (Davenport & Prusak, 1998). Typically, there are two approaches toward knowledge management: codification and personalization (Hansen, Nohria & Tierney, 1999). The first approach assumes that knowledge within the organization can be made explicit and stored within information systems such as knowledge repositories. Hence, knowledge should be retained so that it is available for re-use. The second approach considers organizations as transactive knowledge systems where knowledge is exchanged between individuals (Wegner, 1987). In this approach, knowledge management focuses on stimulating the interaction between individuals so that knowledge diffusion takes place throughout the organization.

The personalization approach has gained more attention of researchers in recent years. Part of this research focuses on the pattern of knowledge interactions that we refer to as knowledge networks (Hanssen, 2002). A visual representation of such a knowledge network consists of nodes that represent the employees of an organization while the links between these nodes represent the knowledge exchanges between these employees. This contextual specification is the main difference between a social network and a knowledge network: a knowledge network is a social network regarded from a knowledge perspective. A useful method for studying these networks is Social Network Analysis (SNA) as it supports both qualitative and quantitative network research (Wasserman & Faust, 1994; Cross & Parker, 2004). Network data that is required for this research is typically collected using surveys or in some instances using interviews. In a survey, a respondent is asked about his/her knowledge exchange relations with his/her colleagues within the organization. Aspects of the relation that can be of interest include the type of knowledge that is exchanged, how it is exchanged, and how frequently it is exchanged. A disadvantage of surveys is that, especially for large surveys, it takes considerable time from the respondent to fill out the survey and that high response rates are required to do qualitative analysis in case studies (Helms, 2007; Teigland, 2002). Consequently, there is hardly any longitudinal analysis of knowledge networks as it requires that a survey is sent out several times during a certain period.

To overcome these issues, some researchers analyze e-mail traffic within organizations as a source for collecting network data (e.g. Tyler, et al., 2005). The advantage here is that because respondents do not need to fill out a survey, the response rate is 100% and longitudinal analysis becomes possible by examining consecutive time frames. A limitation, however, is that the assumption with analyzing e-mail traffic is that e-mail communication is representative for communication that concerns knowledge exchange. Principally, this idea is not wrong as knowledge is an act of personal interaction by means of communication. But this communication does not only take place through e-mail messages. Face-to-face communication is also an important means for getting knowledge across (Lock Lee & Neff, 2004). Furthermore, e-mail messages are not only used for knowledge exchange but for instance also for coordinating tasks and personal messages (Whittaker & Sidner, 1996). Next to e-mail traffic, other communication sources may be applied to overcome the issues of capturing an informal network by means of surveying. One alternative is by means of tracking telephone conversations within an organization. Also, tracking text messages (texting), further referred to as SMS messages (Short Message Service), may be a valuable source for capturing the informal network of the organization.

This paper intends to examine the extent to which networks that are created from sources such as e-mail, telephone and SMS communication are representative for the knowledge network of an organization. We define our research question as follows:

“To what extent are networks, captured from computer mediated communication sources representative for the knowledge network of an organization?”

The need for this research initiative stems from the fact that the analysis of knowledge networks is becoming a more popular instrument in both science and management. Data capturing by means of surveying knows several limitations that data capturing from computer mediated communication sources does not have. The latter form of data capturing always yields a 100% participation, covering the full network, and it supports longitudinal analysis opportunities. If this research can indicate if and to what extent computer mediated communication sources are suitable to represent knowledge networks, it enables new possibilities for analyzing networks for both science and business.

The remainder of this paper is structured as follows. In section 2 this research is embedded in its theoretical background. Section 3 elaborates on the research method and approach. A case study were networks are captured and compared is introduced and a comparison approach of the networks is elaborated upon. In section 4 the results of the case study are provided, based on the proposed measuring and comparison approach. In section 5 our findings are discussed and conclusions and limitations are provided.

2 THEORETICAL BACKGROUND

A knowledge network concerns the knowledge management activities (e.g. knowledge creation or sharing) that take place among people in an organization. When focusing on a particular knowledge management activity, several types of knowledge networks can be distinguished. Two types of knowledge networks that are often distinguished in literature include learning networks (cf. Skerlavaj, Dimovski, Mrvar & Pahor, 2008) and advice networks (cf. Borgatti & Cross, 2003). Both types of knowledge network are included in this research and described in more detail below. Furthermore, the role of communication in knowledge exchange is briefly explored, which finally leads to the idea to use communication data stored by technology supported media as a source for collecting data on knowledge networks.

The traditional, cognitive view on learning assumes that learning is a mental process within the heads of individuals (Hustad, 2007). In this view, learning is separated from doing in practice and therefore neglects what can be learnt through experience and collaboration. More recent views consider learning as a social process of mutual engagement and relate learning explicitly to practice. Two major accounts in this field are the work by Lave & Wenger (1991) and Brown & Duguid (1991). Based on their studies, they introduced the concept of Situated Learning and Learning in Working respectively. The concept of situated learning is based on master-apprenticeship relationships where apprentices learn and master a practice through legitimate peripheral participation. Peripheral participation means that the apprentices start participating by performing relatively easy tasks and with low risk to the practice, i.e. in the periphery of the practice. During the execution of his tasks, the apprentice engages with and is coached by more experienced practitioners in the practice. If an apprentice is successful, i.e. he is learning, he gets more responsibilities until he finally becomes a master himself.

In this research, we refer to the learning relations between employees in an organization as knowledge networks (Skerlavaj et al., 2008; Palazzolo et al., 2006). Knowledge that is exchanged in learning relations typically involves tacit knowledge and consists of skills, experience and attitudes. This makes knowledge exchange difficult and therefore not every type of knowledge exchange is as effective as another. More active learning approaches, e.g. guided problem solving or guided observation, are preferred as they result in richer knowledge transfers from the master to the apprentice (Leonard & Swap, 2005; Davenport & Prusak, 1998). Richer knowledge transfers results in a higher level of knowledge exchange and therefore contribute to a deeper understanding of the practice. The goal of learning networks is to increase and preserve the knowledge and competence level of employees in the organization, which should ultimately result in a better performance of the organization (Skerlavaj et al., 2008).

Advice networks refer to the idea that employees are dependent on the knowledge of others to execute their job (Cross & Parker, 2004). In that case, it is important to know who knows what and to have access to these people so that they can be asked for advice when needed (Borgatti & Cross, 2003). Cross, Borgatti & Parker (2001) defined five different types of advice that can be sought: Solutions, Meta-knowledge, Problem reformulation, Validation, and Legitimation. These types indicate the intention for seeking advice from a colleague. Providing advice takes place by exchanging knowledge, however, this knowledge exchange is considered to be different from knowledge exchange in a learning network. In the case of an advice network, the goal is to transfer just enough knowledge so that the advice seeker can solve his problem. Hence, more passive learning approaches for knowledge exchange can be used such as directives, rules of thumb or pointers to information sources (Leonard & Swap, 2005). Besides knowing who knows who and having access, it is also important that you can tap into this knowledge quickly (Cross & Parker, 2004). The speed of knowledge exchange is referred to as velocity (Davenport & Prusak, 1998). It is defined as the time between contacting a colleague and finally receiving the requested knowledge from this colleague, either directly from him or via him from another colleague. The higher the velocity of the knowledge exchanges in the advice network, the better it is for the job performance (Hansen, 2002).

Communication is a vital mechanism when it comes to exchanging knowledge in learning as well as advice networks (Palazzolo et al., 2006). It is through communication, consisting of for example discussions and asking questions, that an apprentice can learn from a master. Furthermore, communication is also the basis for asking advice from colleagues. Several media are available for communication and hence for knowledge exchange in learning and advice networks. Basically, two types of media can be distinguished: Face-to-face contact and technology supported media. According to media richness theory (Daft & Lengel, 1986), the selection of the right medium depends on the richness of the knowledge that needs to be exchanged. Consequently, it might be wise to use different media for learning and asking for advice as the richness of the knowledge transfer in both cases is different. Research shows that people have a strong preference for face-to-face contact when it comes to exchanging knowledge (Cross et al., 2001; Smith & McKeen, 2003; Lock Lee & Neff, 2004). All studies reported that computer supported media such as e-mail, telephone or intranet have a lower preference. It is not just that face-to-face contact is the best medium per se but also that other factors are involved why people prefer face-to-face contact. These factors include trust and social cues for example (Wenger, McDermott & Snyder, 2002; Hooff, De Ridder & Aukema, 2004). But it is not just a matter of selecting the best medium, but using several media at the same time as they reinforce and support each other (Davenport & Prusak, 1998). Hence, it is likely that people will use several computer supported media to support face-to-face contact. Based on this assumption, it might be worthwhile to explore to what extent data about knowledge network relations can be retrieved from the computer supported media that store data about communication.

E-mail is a computer supported medium that is more frequently used to capture the social network of an organization (e.g. Tyler, Wilkinson & Huberman, 2005) and a variety of tools exist that support capturing a social network from e-mail data (e.g.: Gloor (2004), Edwards (2005), Mika (2005) and Viegas, Golder & Donath (2006)). E-mail is argued to be a plausible source for capturing a social network. Farnham , Portnoy & Turski (2004) for example reveal that the people we mail most are also the people we tend to work with most. This does, however, not argue for the fact whether e-mail data may also be applied to capture a knowledge network. Hence, it is relevant to investigate to what extent e-mail data, along with other computer mediated communication sources, such as telephone communication and SMS messages, are plausible as sources to capture the knowledge network of an organization.

3 RESEARCH METHOD

3.1 Approach & Sample

In order to examine the research questions, a comparison was made between an advice and a learning network on the one hand and 3 communication networks on the other hand, derived from e-mail traffic, mobile phone calls and SMS messages. The choice for these networks stems from the availability of data in our sample. A case study was conducted in a Dutch consultancy firm in the IT services sector. The firm consists of 68 employees, of which 41 were included in our sample due to their participation in the survey. Of these 41 employees, 10% is female. Moreover, the sample is divided over 6 functional areas (e.g. management, consultancy) and 3 levels of seniority (junior, medior, senior). The case study was conducted in June 2008, a non-holiday period, boosting the representativeness of the networks while no colleagues were unavailable. The scope of the data collection was 1 month. Most employees in our sample are geographically separated in their daily work. Therefore, these employees heavily rely on computer mediated communication media such as e-mail, telephone and SMS to communicate with each other.

3.2 Data collection

The data for the advice and the learning network was collected by means of an online web-survey that was specifically created for this research. In the survey, employees were asked to indicate to what extent they give advice to each other and to what extent they learn from others. Both questions could score on a 5-point scale, ranging from "sporadically" to "intensively". From the survey results, two adjacency matrices were created: an advice network and a learning network. The scores that each *1* respondent provided for *1..n* colleagues were placed in the cells of an adjacency matrix where each respondent is represented by a row and each colleague by a column. The cells were the row and column match the same person were not taken into account. While no advice or learning (score: 0) was also denoted in the adjacency matrix, a matrix is always squared. Eventually, before the calculations were performed, the 2 matrices were recoded. The 5 points in the scale were reduced to 4 points, cancelling out the 1 on the scale, leaving a scale of 2-5. This was done after an examination of the scores in the web-survey. About 50% of the respondents indicated a connection to all other respondents of at least 1 on the scale, meaning that these respondents indicated that they at least sporadically contacted all other respondents. The other 50% of the respondents did not indicate this connection of at least 1 on the scale to all other respondents. This distortion was solved by removing the 1 on the scale. The communication networks (e-mail, telephone and SMS) were not recoded.

For the respondents that participated in the survey, we also collected data about their e-mail, telephone and SMS communication. For this purpose, the Exchange server was accessed to extract one month of e-mail communication data and mobile phone bills were accessed to extract telephone and SMS communication data. Both the data from the Exchange server and the mobile phone bills were applied in a data mining application that was specifically designed and developed for this research, called ESNE: E-mail Social Network Extraction. The application uses the header data of e-mail messages (the "from" and "to" headers). The content of the messages (body data) was discarded due to privacy regulations in our organization of study. Also, the application supports filtering of the e-mail messages. Filtering was applied in various ways. First of all, the data was filtered for a specific time frame of 1 month. Moreover, an upper bound was defined for mass e-mails. Messages that were sent to over 20 recipients were filtered out from our research. It is argued that these e-mails do not represent personal communication as is the case in an advice and a learning network. No lower bound was defined. Different from other tools, our application also filtered out automatically generated messages (e.g. an out-of-office reply) and all senders and recipients external to the company, leaving only the communication between employees, as again is the case in an advice and a learning network. Similar to other tools (e.g. Holzer, Malin & Sweeney (2005) and Bird et al. (2006)), the application also supports finding aliases. The application scanned all employees on their first and last name and provided possible aliases for each employee (i.e. different mail addresses). All possible aliases were manually linked to an employee or discarded by a manager from the organization. The application itself does not support the visualization of a social network from the data but it is capable of creating adjacency matrices from the e-mail data in the format of the social network analysis software used in this research (.ntf file to import in Cyram Netminer 3.30a). The .ntf file contains both the adjacency matrix and an attribute table containing actor attributes that were derived from employee data managed in the application. This way, an adjacency matrix was created from the filtered e-mail data (including aliases) from June 2008. The weight in the adjacency matrix is expressed by the amount of e-mail messages exchanged between two actors.

Likewise, two adjacency matrices were created from the telephone and SMS data. The application filtered the telephone data to exclude all but mobile phone calls from and to the employees of the focal organization. Also, calls that lasted less than 10 seconds were filtered out. Concerning the SMS data, only the messages that were sent from and to employees were included. The weight in both matrices is again expressed by the amount of calls or messages exchanged between two actors. All matrices i.e. the advice and learning matrices from the web-survey and the e-mail, telephone and SMS matrices from the analysis tool, were manually combined to one file containing the 5 matrices, identical in size and actors, and one attribute table to be used in our social network analysis software.

3.3 Measures

In order to investigate the differences between the networks, a means to compare the networks is required. In the comparison process, the networks that were captured by means of the web-survey were treated as a baseline. It is argued that these networks represent the actual advice and learning network of the organization, as these are the only networks where the employees indicated their relations themselves. In comparison: the e-mail, telephone and SMS networks are a result of communication, moreover than an indication of relations by the employees themselves.

For the comparison between the networks, a two-way comparison format is proposed. First, the networks are compared by means of correlating the matrices. Correlation coefficients can indicate the extent to which the matrices of the networks are similar to each other. The correlation coefficients can be calculated over either the non-weighed (binary) data and the weighed data. The first calculation indicates similarity when only observing whether actors are tied or not. The second calculation indicates the similarity when also taking into account the weight of links between actors. The correlation coefficients for the non-weighed matrices are calculated using the Jaccard coefficient. This coefficient is based on only the existing relations in a matrix and neglects the non-existing relations (i.e. it matches the 1 and neglects the 0). For the weighed matrices, the Pearon's correlation coefficient is applied. For all correlation measures, a QAP permutation test (Borgatti, Everett & Freeman, 1992) is applied with 2.500 iterations in order to support the significance of the correlation scores.

In the second way of comparing the networks from our comparison format, the networks are compared by means of calculating and comparing network properties that tell something about the structure of the networks. By comparing the networks by means of their properties, further insight can be gained in the equivalence of the networks. For comparing the network properties, we use a number of well-known network measures (derived from Hanneman & Riddle (2005)) that cover different aspects of network structure. An overview of the the network properties that are examined is provided in table 1. For a more elaborate description of the network properties, the reader is referred to Hanneman & Riddle (2005)).

	Description
Basic Demographics	
Number of Links	Total amount of links that exist between the actors in the network (e.g. 50)
Average Degree	Average amount of links per actor in the network (e.g. 5)
Connection	
Mean Distance	Network average of geographic path distance between 2 actors in the network (e.g. 2,2)
Diameter	Network maximum of geographic path distance between 2 actors in the network (e.g. 5)
Density	Ratio of existing links relative to the amount of possible links (e.g. 35%)
Connectedness	Extent to which the network is a single component (e.g. 35%)
Embedding	
Reciprocity (Dyad method)	Extent to which relations are dyadic (e.g. 35%)
Transitivity	Extent to which relations are triangular (e.g. 35%)
Centrality	
In-Degree Centralization	Degree of variance in in-degree centrality opposed to a perfect star network (e.g. 35%)
Out-Degree Centralization	Degree of variance in out-degree centrality opposed to a perfect star network (e.g. 35%)
Clustering	
Clustering Coefficient	Extent to which connections overlap per actor (my link is also your link) (e.g. 35%)

Table 1. Network properties used to compare the networks

4 RESULTS

4.1 Matrix correlations

In table 2 and 3 below, an overview is provided of the correlation coefficients between all five networks. For the QAP permutation test, in all cases the *p >= observed* values were .000, indicating that all results are significant. For the Pearson correlations of the weighed matrices, the significance is expressed by either * or **.

As can be derived from table 2 and 3, the correlation coefficient between the advice and learning network indicates that both networks have no specifically high overlap. From this fact we may conclude that it is plausible to interpret the correlations of the e-mail, telephone and SMS networks to the advice network separate from the correlations of those communication networks to the learning network. A clear decreasing trend is visible for the similarity between the survey networks (advice and learning) and the communication networks, decreasing from mail, to telephone, to SMS. This trend applies for both the non-weighed and weighed data and for both the advice and learning network. Another result from the calculations is the fact that the weighed communication network matrices show higher scores than the non-weighed communication network matrices, meaning that e.g. the e-mail network is more similar to the advice and learning network if the weight of the links is taken into account. The e-mail, telephone and SMS networks tend to be more similar to the advice network than to the learning network. However, these differences are only minor.

	Advice	Learning	Mail	Phone	SMS	Extended
Advice						
Learning	.376					
Mail	.409	.397				
Phone	.212	.212	.312			
SMS	.074	.079	.085	.202		
Extended	.389	.386	.502	.184	.054	

Table 2: Jaccard coefficient calculations between the non-weighed networks

	Advice	Learning	Mail	Phone	SMS	Extended
Advice						
Learning	.458**					
Mail	.419*	.383*				
Phone	.287	.230	.487**			
SMS	.132	.098	.199	.413*		
Extended	.499**	.456**	.830**	.438*	.214	

Table 3: Pearson correlation coefficient calculations between the weighed networks

4.2 Extended mail network

From our findings from the matrix correlations, we learned that of all communication networks, the e-mail network is the most similar to the advice and learning network. Therefore we decided to extend the research concerning the similarity between the advice and learning network on the one hand and the e-mail network on the other hand. It is argued that the timeframe of one month that is applied in this research may yield that the e-mail network is less similar to the advice and learning networks than it could be if the timeframe is extended. Therefore, the timeframe of the e-mail network was extended to 6 months, from January to June 2008. From this data, a new network, the extended e-mail network, was constructed using the data mining application (ESNE). The extended e-mail network was then correlated against the advice and learning network. Again, the $p >= \textit{observed}$ values were .000 in all cases, indicating that all results are significant. The results from these calculations are incorporated in table 2 and 3 above.

The results show a different outcome for the non-weighed than for the weighed data. The non-weighed data shows that the extended e-mail network is less similar to the original e-mail network that consists of only one month of data. However, the difference between the scores from the non-weighed and the weighed data are minimal. On the other hand, the weighed data does indeed show that the extended e-mail network is more similar to both the advice and learning networks than the original e-mail data of one month.

4.3 Network properties

In table 4 an overview is provided of the scores from 11 network properties that are commonly used in social network analysis. The scores are calculated for all basic weighed networks (i.e. the extended e-mail network is excluded from our scope here).

	Advice	Learning	Mail	Phone	SMS
Basic Demographics					
Number of Links	464	465	493	193	57
Average Degree	11	11	12	5	1
Connection					
Mean Distance	1,8	1,8	1,8	2,1	2,4
Diameter	4	4	4	5	5
Density	28%	28%	30%	12%	4%
Connectedness	81%	90%	100%	37%	6%
Embedding					
Reciprocity (Dyad method)	36%	36%	76%	30%	43%
Transitivity	54%	54%	53%	35%	26%
Centrality					
In-Degree Centralization	38%	71%	44%	39%	14%
Out-Degree Centralization	71%	48%	46%	37%	12%
Clustering					
Clustering Coefficient	72%	71%	69%	59%	21%

Table 4: Network properties and scores

The network properties displayed in table 4 show different scores for the different networks. For most network properties, the same trend can be visualized as with the matrix correlations. Of all communication networks, it is again the e-mail network that most resembles the advice and learning networks. The telephone network is less similar to the advice and learning networks and the SMS network even less. This trend does, however, not apply for the reciprocity network property. An explanation for the deviating reciprocity value in the e-mail network may be that of all forms of communication studied in this research, e-mail is typically a medium of bilateral communication, i.e. an e-mail is typically replied to with another e-mail. This way of communicating is not found in media such as telephony or in an advice or learning network, where one instance of communication already involves both sender and receiver. The matrix correlations showed that the e-mail network, which is the communication network that most resembles the surveyed networks, is more similar to the advice network than to the learning network. In the case of the network properties, however, the e-mail network is more similar to the learning network than to the advice network. Again, these differences are only minor. This does, however, not apply for the centralization properties, where the in-degree centralization index of the e-mail network is far more similar to the advice network and the out-degree centralization index of the e-mail network is far more similar to the learning network.

5 DISCUSSION & CONCLUSIONS

5.1 Discussion & conclusions

This paper intended to examine to what extent computer mediated communication in organizations may be representative sources for capturing and analyzing organizational knowledge networks. As the analysis of organizational networks is becoming an increasingly more important management instrument, there is a need to continuously improve the analysis method. While capturing network data by means of surveying knows several limitations, the analysis of computer mediated communication sources may provide a promising alternative. In the Dutch IT services organization were we conducted our case study, 6 networks were captured: the advice and learning network by means of surveying and 4 communication networks from e-mail traffic (1 month and 6 months in length), telephone conversations and SMS (text) messages. Consequently, a comparison between the networks was conducted by means of two comparison approaches: correlating the network matrices and comparing basic network properties, applied in social network analysis. Results from the matrix correlations show that only the e-mail network (both the original and the extended network) is significantly representative for both the advice and learning network. The telephone and SMS network are only slightly representative to the advice and learning network. The results from the network property calculations support the findings from the matrix correlations to a large extent. A secondary finding is the fact that the extended e-mail network has a mixed effect on the quality of representativeness of the original e-mail network. While the weighed extended e-mail network is more representative to the learning and advice network as its weights are more representative, the non-weighed extended e-mail network is less representative for the advice and learning network. This is probably caused by a distortion due to introducing new relations in the extended e-mail network that were not present in the original e-mail network and also not in the advice and learning network. This distortion may be removed by defining a minimum amount of messages sent between two actors before including the relation in the network (recoding the data). Although this examination was only conducted in one organization, the richness of the data proved worth to investigate how the computer mediated communication networks resemble the advice and learning network that provided a baseline for the knowledge networks in the organization of our case study. We may conclude from our research that a network based on e-mail traffic proves to be a valid representation for a knowledge network when conducting knowledge network analysis if surveying the focal organization is not an option.

5.2 Limitations

Probably the most important limitation on our research is the fact that this research was conducted in only one organization. Therefore, we cannot conclude on the repeatability of our findings in other organizations. It is, however, imaginable that it is quite a challenge to find multiple organizations that are willing to participate in a survey and also provide access to their Exchange server (e-mail) and to provide mobile phone bills (telephone and SMS). This is the reason that this research was addressed as an exploratory case study research. Another limitation is that the scales used in the data capturing process for the 6 matrices were not normalized. The advice and learning networks consist of a 5-point scale, whereas the e-mail, telephone and SMS networks were based on the amount of messages or calls. However, the analysis of the matrix correlations lowers the effect of this limitation as the coefficients calculated over both the weighed and non-weighed networks are similar to a large extent. A final limitation is the fact that the telephone and SMS networks could not be captured for 100% of the data. This is due to the fact that the telephone bills were partially concealed. This was done by the provider of the telephone network and cannot be altered. In the telephone network 20% of the data was removed and in the SMS network 9% of the data was removed due to concealed data (anonymous calls and SMS messages). Because the blocked entries on the telephone bills are spread over all of the actors, it is false to conclude that the measured indicators deviate by 20% and 9%. The percentages only decrease the amount of calls and messages, they do not remove 20% and 9% of the links. From the existence of concealed entries it is, however, evident and fully in line with the findings of this research that telephone and SMS networks should not be favored as a surrogate for the advice and learning network of an organization.

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