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"WHO IS KEY...?" - CHARACTERIZING VALUE ADDING USERS IN ENTERPRISE SOCIAL NETWORKS

Katharina Berger
University of Regensburg, Regensburg, Germany, katharina.berger@wiwi.uni-regensburg.de

Julia Klier
University of Regensburg, Regensburg, Germany, julia.klier@wiwi.uni-regensburg.de

Mathias Klier
University of Regensburg, Regensburg, Germany, mathias.klier@wiwi.uni-regensburg.de

Alexander Richter
University of Zurich, Zurich, Switzerland, a.richter@unibw.de

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“WHO IS KEY...?” – VALUE ADDING USERS IN ENTERPRISE SOCIAL NETWORKS

Complete Research

Berger, Katharina, University of Regensburg, Regensburg, Germany, katharina.berger@ur.de

Klier, Julia, University of Regensburg, Regensburg, Germany, julia.klier@ur.de

Klier, Mathias, University of Regensburg, Regensburg, Germany, mathias.klier@ur.de

Richter, Alexander, University of Zurich, Zurich, Switzerland, arichter@ifi.uzh.ch

Abstract

Whereas the use of Enterprise Social Networks (ESN) is a pervasive topic in research and practice, both parties are still struggling to come to a better understanding of the role and impact of ESN in and on knowledge-intensive corporate work. As a part of this phenomenon, employees who communicate their knowledge in ESN helping other users to do their daily work play a decisive role. We need to come to a better understanding of the role and behaviour of such value adding users. This is a prerequisite, for example, for understanding knowledge support hubs or for enabling more effective internal information and knowledge sharing. Against this background, we investigate the structural characteristics of value adding users in ESN using qualitative text analysis and Social Network Analysis. Based on a large scale dataset of a global consulting company using the ESN Yammer.com we analyse the social relationships of value adding users. We confirm their significant position and draw conclusions for research and practice.

Keywords: Enterprise Social Network, Social Network Analysis, Social Software, CSCW.

1 Introduction

In recent years, many organizations have started to implement Enterprise Social Networks (ESN) in their companies to foster collaboration, communication, and knowledge-sharing among employees (Aral et al., 2013; von Krogh, 2012). According to a recent study, more than 90% of all Fortune 500 companies had partially or fully implemented an ESN by the end of 2013, a 70% increase compared to 2011 (Deloitte, 2013). As more and more employees are using ESN in their daily work practices, there is an increasing demand to better understand the role and impact of these social technologies in and on knowledge-intensive corporate work (Bharadwaj et al., 2013; Herzog et al., 2013; Richter et al., 2013). First studies have shown that ESN can for instance support expert finding, information seeking, idea sharing, or team coordination, depending on the existing work practices (DiMicco et al., 2008; Thom-Santelli et al., 2011).

In this context, it has been argued that analysing the network structure of users of social networks in view of the value add bears a huge potential (Katona et al., 2011). The underlying idea is that understanding the network structure of individual users helps to determine the key users with respect to the said value add (Trusov et al., 2010). In the context of ESN, these users are in the managerial interest particularly with respect to understanding knowledge support hubs, that means employees helping other users with their daily work, or to designing targeted internal communication strategies, for instance in enterprise transformation programs. For the understanding of key users in general, literature in the context of Social Network Analysis indicates that both users' connectivity, for example the number of followers (e.g., Staab et al., 2005), and users' communication activity (e.g., Cheung and Lee, 2010), for example the number of messages, are particularly important. However, even though these studies provide meaningful insights in the context of social networks in general, we cannot simply confer these insights to specific ESN, since the interpretations of important nodes or key users strongly depend on the particular context (Borgatti, 2005; Borgatti and Everett, 2006; Freeman et al., 1980). In addition, most of the previous studies focus on mere social structures (e.g., Borgatti, 2006) without incorporating the value add of a user into their investigations.

Therefore, the aim of this paper is to investigate the structural characteristics of value adding key users in the context of ESN and thus to distinguish these users. In so doing, we address the following research question: How can value adding key users be distinguished with respect to their structural characteristics like for example the number of followers, group memberships, or the centrality in ESN? To answer this question, we analysed a large scale dataset of a global consulting company using the ESN Yammer.com. Our results indicate how it helps to not only consider the social structures of users in ESN (by analysing centrality measures), but rather try to incorporate the idea of the value add of a user into our analysis. We also illustrate how value adding key users are characterized in terms of their connectivity in the social graph as well as the activity graph. These insights can help organizations to get a deeper understanding of the role and characteristics of key users in ESN. Given that social technologies like ESN are a core phenomenon of the 21st century at the heart of the IS discipline, our findings contribute to developing a more refined understanding of ESN in general.

The remainder of this paper is structured as follows: In Section 2, we review the existing literature. Section 3 describes the research method, the case setting, and the data collection and analysis process. In Section 4, we present our findings based on a qualitative text analysis and Social Network Analysis of the dataset of the ESN Yammer.com at a global consulting company. In Section 5, we critically discuss implications and limitations of our work and provide directions for further research. Finally, we conclude with a brief summary of our results.

2 Theoretical Background

In this section, we focus the relevant literature on ESN and their underlying network structure. We also review prior research on the role and identification of key users in social networks. Drawing on the existing literature, we finally identify the research gap.

2.1 Enterprise Social Networks

In recent years, we have seen a continuously increasing demand for ESN to support knowledge transfer and collaboration in companies (e.g., Benbya and van Alstyne, 2010; Bughin and Manyika, 2007; Haefliger et al., 2011). Many organizations started to experiment with the implementation of ESN as a particular phenomenon in the social media ecosystem of large organizations (Riemer et al., 2012a). Some leading companies (such as IBM) have been using the power of ESN to transform their internal organizations from "command-and-control to connect-and-coordinate" (Agarwal et al., 2008). Thereby, ESN platforms "put emphasis on social relationships, interactive communication and adhoc sharing" (Riemer et al., 2012c, p. 5). While some organizations decided to develop own solutions (e.g. Siemens), others have opted for on-premise vendor platforms (e.g. Jive SBS, IBM Connections) or web service solutions (e.g. Yammer.com, Salesforce Chatter).

Prior research on ESN was conducted, for example with the goal of understanding how employees build relationships (DiMicco et al., 2009), how ESN dynamically emerged in organizations (Riemer et al., 2012b), and why people voluntarily contribute knowledge and help others through electronic networks (Wasko and Faraj, 2005). Further research focuses on investigating the potential benefits of ESN in the corporate realm, including information seeking, expert finding, problem solving, work coordination, and opinion sharing (Brzozowski, 2009; Richter and Riemer, 2013; Thom-Santelli et al., 2011). Research findings also show that ESN foster user participation in creating web content (e.g., Holtzblatt et al., 2010; Ip and Wagner, 2008) and allow for new ways of connecting, interacting, and communicating with other people (e.g., DiMicco et al., 2009; Zhang et al., 2010). In this context, research has been indicating that ESN have implications not only for company performance, but also with respect to career paths of employees. Wu (2013), for instance, studied the impact of introducing an ESN in the consulting division of a large information technology company. Specifically, he found that the ESN transformed network positions of individuals over time and that there were significant correlations with both job performance and job security (Wu, 2013). Moreover, Matthews et al. (2013) analysed how leaders enhance the value of their communities. Further work in this context includes research aiming at understanding how diversity influences collaboration, teaming, and innovation (Muller et al., 2012). In addition, as more and more employees are using ESN, there is an increasing demand to understand how the use of these technologies can be evaluated (Herzog et al., 2013; Lehner and Haas, 2011; Muller et al., 2009; Richter et al., 2013). To sum up, there is a growing body of knowledge that addresses a huge amount of research topics, since ESN have become an important phenomenon in the corporate context finding increasing attention in recent years.

2.2 Enterprise Social Networks and their structures

Latest research has shown that the network structures of ESN play a decisive role in understanding and explaining user behaviour in ESN (Wang et al., 2013). Golder and Yardi (2010), for example, found that the structural characteristics transitivity and mutuality are significant predictors of the desire to form new ties in microblogging services. In general, structural characteristics have been extensively studied to describe, for instance, human behaviour in multiple social networks (Shapiro and Varian, 1999). The structure invoked by the binary connections among users in ESN can be mostly perceived as “a set of actors connected by a set of ties. The actors (often called ‘nodes’) can be persons, teams, organizations, concepts, etc. Ties connect pairs of actors and can be directed (i.e. potentially one-directional, as in giving advice to someone) or undirected (as in being physically proximate) and can be dichotomous (present or absent, as in whether two people are friends or not) or valued (measured on a scale, as in strength of friendship)“ (Borgatti and Foster, 2003, p. 922). These nodes and ties determining the network structure can be analysed by Social Network Analysis (SNA) (Trier, 2008; Wasserman and Faust, 2009) that forms the theoretical basis for understanding the network structure of social networks, and ESN in particular.

Social Network Theory implies that not all nodes in a social network can be considered as equal. They largely differ in terms of their connectivity (e.g. number of friends), their communication activity (e.g. number of messages) as well as their frequency, volume, and quality of the user-generated content (Trusov et al., 2010). For the context of ESN, earlier research notes that only a few individuals receive a majority of the attention in ESN (Yardi et al., 2009) and that there is often a small number of very active users as opposed to a large number of rather passive users (so called lurkers) (Muller et al., 2010; Yeow et al., 2006; Yuqing et al., 2007). Therefore, from a management perspective, it is essential to know who is a “key user” to enable, for instance, better expert identification or more effective communication strategies (e.g. a targeted communication campaign in a large organization) by addressing users on purpose. Goldenberg et al. (2009), for instance, found that key users in a social network have a decisive role in diffusion and adoption processes and can be used as an efficient target for word-of-mouth campaigns. Literature indicates that a person’s importance can be inferred from his or her structural position in the network (Iacobucci, 1996). The most common concept to determine the importance of a user in a social network is network centrality. For the specific context of social networks, several network measures were developed to better capture the "centrality" of individuals and to identify prestigious nodes in the network (Bonacich, 1987; Wasserman and Faust, 2009). Some of the most commonly used centrality measures include degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality (Bonacich, 1972; Freeman, 1979). Further research on the identification of central nodes was done with respect to their social position in the network, which can be determined, for example, by means of equivalence relations (e.g., Brynielsson et al., 2012), in combination with workflow management (van der Aalst and Song, 2004) or cluster analysis (e.g., Zygmunt et al., 2012).

In the related research context of online social networks (e.g. Facebook), there are first articles using these centrality measures to identify influential users, for example to foster more effective advertising or marketing strategies (e.g. viral marketing campaigns or targeted marketing) (e.g., Heidemann et al., 2010; Hinz et al., 2011; Trusov et al., 2010). In addition, approaches for the identification and understanding of important nodes can be found not only in Social Network Analysis, but also in many other fields as for instance in biology for the identification of genes (e.g., Özgür et al., 2008) or in scientometrics for the ranking of scientific journals (e.g., Bollen et al., 2006). However, the interpretations of important nodes or key users highly depend on the particular context (Borgatti, 2005; Borgatti and Everett, 2006; Freeman et al., 1980).

Altogether, researchers emphasize the importance of both the network structure of ESN and the specific context for the interpretation of central nodes. To date, to the best of our knowledge, there is not a single approach in the context of ESN describing the characteristics of value adding key users and thus bringing together concepts from both Social Networks Analysis and value based thinking. Therefore, the aim of this paper is to investigate the structural characteristics of value adding key users in ESN. Our contribution for theory and practice is threefold: First, we do not only consider the mere social structures of users in ESN (by analysing centrality measures), but rather try to incorporate the idea of the value add of a user into our analysis. Second, in that realm, we illustrate that most of the messages which receive likes and bookmarks have a professional purpose. Finally, we show how value adding key users are characterized in terms of their connectivity in the social graph as well as the activity graph.

3 Research Method

In this section, we provide an overview of the setting and the data collection. Then, we discuss the analysis process and the applied methods, qualitative text analysis and Social Network Analysis.

3.1 Setting

The study was conducted at a large multinational consulting company, in the following called BIG, with more than 100,000 employees in more than 30 countries worldwide. In 2008, the first BIG employee started to use the ESN Yammer.com. Yammer itself had been launched the same year. Yammer is a cloud service that means it is not installed on companies' webservers, but can be accessed from any web browser. Yammer is organised around networks, with one network typically representing one company. Anyone can create a network for their company by registering with their email address on the platform. New users can join their Yammer network by registering with their corporate email address, which serves as an identifier. When Microsoft acquired Yammer in 2012, the service was used by more than 200,000 companies worldwide. The functionalities of Yammer always resembled those of Twitter.com and have continuously been advanced. From the beginning, Yammer was based on the "follower"-principle, i.e. users choose whom they follow and see who follows them.

Thus, the resulting network is directed and displayed as a list sorted by name, as part of an employee's profile. In addition, users can create groups that form sub networks of the entire ESN, for example based on certain topics like "Cloud Computing" or "IT Security Matters". Further early platform features included profile information, options to send direct messages, and the possibility to like and bookmark posts. These functionalities are of special interest for our study.

3.2 Data collection and preparation

BIG provided us with the complete Yammer dataset, ranging from September 2008 to July 2010, for 10,434 unique users of the platform. 7,304 of these users followed at least one other user of the platform. Moreover, the data contain 101,132 messages that were posted inside the ESN over this period. These messages were written by a total of 9,806 users. Each message consists of metadata such as a message ID, a reply ID, a thread ID, a user ID, and the content of the message. In Yammer, a message is either a reply to another message that inherits the thread ID of this original message, or it is a new message commencing a thread with a new ID. Thus thread IDs can be used to analyse related communications in the data. Furthermore, the data comprises 14,946 likes in reply to messages that were sent by 984 users of the platform. In addition, the Yammer dataset includes 599 bookmarks that were stored by users for later retrieval. Finally, the datasets contains information about 282 sub-groups to which the users were belonging. To ensure confidentiality, all personally identifying information (user names and client names) had been removed prior to handing over the data.

3.3 Data analysis and measures

Our initial study on this topic aims to investigate the structural characteristics of value adding users in ESN to distinguish these users. By this means it intends to provide first insights on their structural positions in the network which can serve as a starting point for further analyses (cf. Section 5.2). At BIG, the ESN was amongst others used for knowledge transfer among employees. Against this background, those users of the ESN are regarded as value adding who contribute and communicate their knowledge in the ESN thus helping other users to work more successfully and efficiently. Yammer.com provides functionalities to like and bookmark posts in terms of messages by other users which are deemed helpful. Hence, value adding contributions in the ESN receive likes and bookmarks. One may assume that the vast majority of the users' likes and bookmarks in the ESN have a professional background marking important and value adding contributions. Against this background, in our specific context likes and bookmarks seem to be better suited as measurements for key users as compared to the mere number of written messages or followers which do not provide such a concrete indication with respect to a user's value add. Thus, for our data analyses we define and identify key users as those users of the ESN whose messages received the most likes and bookmarks.

To substantiate this definition of key users for our setting, we applied a qualitative text analysis (e.g., Bryman and Bell, 2007). Whereas the application spectrum of qualitative text analysis is already quite broad (a still broader term is qualitative content analysis), our aim was to find out whether the vast majority of likes and bookmarks had a professional background to qualify them to be considered as value adding (from the perspective of BIG). To do so, we selected all messages with at least one like or one bookmark from our dataset, respectively. All messages automatically generated by the system (e.g. "a new user has joined the network") as well as messages written in another language than English or German were excluded. The latter was due to the language skills of the researchers and concerns only a small proportion of the messages with at least one like (5%) or bookmark (2%). The final dataset contained 8,142 messages with at least one like and 450 messages with at least one bookmark. A team of three researchers manually coded the messages to one of the two categories "professional" and "non-professional" (Miles and Huberman, 1994). Each message was screened independently by at least two persons. In the event of any disagreement we decided on the best fitting genre in a team discussion. The reliability of agreement between the researches was measured with Fleiss' Kappa (Fleiss, 1971). We observed a value for Fleiss' Kappa of nearly 83%. According to Landis and Koch (1977) this reflects an almost perfect agreement between the team of researchers.

To investigate the structural characteristics of the key users based on our dataset, we apply Social Network Analysis (SNA). Social Network Analysis has been intensively used in IS research, for example to investigate users' network creation behaviour (e.g., Krasnova et al., 2010) or social capital as a result of the usage of an OSN (e.g., Ellison et al., 2007). According to Freeman (2000, p. 350), Social Network Analysis "involves theorizing, model building, and empirical research focused on uncovering the patterning of links among actors". In this context, there exist several measures to quantify the centrality of a node within a network. The most common centrality measures are degree centrality, closeness centrality, betweenness centrality (Freeman, 1979), and eigenvector centrality (Bonacich, 1972). An ESN can be represented as a graph with a set of nodes (users) and a set of edges (ties) linking pairs of nodes (Wasserman and Faust, 2009). The edges may be directed or undirected and can represent either social links like friendship relationships (social graph) or communication activities (activity graph) like messages amongst users (e.g., Adamic and Adar, 2003; Bampo et al., 2008; Heidemann et al., 2010). To get profound insights into the structural characteristics of key users in ESN, we base our research on both the social graph and the activity graph of the ESN. The social graph consists of the follower relations between the users (i.e. who follows whom) as social links and is represented as a graph with 10,434 nodes and 137,550 directed edges. The activity graph is formed by the users' communication activities, i.e. all messages among the users, with some messages like group or status messages having more than one receiver. It consists of 10,434 nodes and 9,645,500 directed edges. For the network analysis, we used the igraph package[1] for *R* to calculate the degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality for each node of the social as well as of the activity graph.

4 Findings

This section is dedicated to the results of our study. First, we focus on the results of the qualitative text analysis. The second part concentrates on the results of the Social Network Analysis.

4.1 Results of the qualitative text analysis

The results of the qualitative text analysis reveal that the content of most of the messages which received likes and bookmarks have a professional purpose (cf. Figure 1). More specifically, distinguishing only the categories "professional" and "non-professional", we observed that about 81% of the messages which were liked and 94% of the messages which were bookmarked have a professional background. The professional messages included, for example, hints on (new) ESN functionality (e.g. "*Yammer also offers kind of auto-completion when entering a hashtag to reduce different spellings or namings*"), further information on work-related topics (e.g. "*Cloud security paper from the point of view of using clouds as massive computational resources published by the European Space Agency. http://www.enisa.europa.eu/act/rm/files/deliverables/cloud-computing-risk-assessment*") as well as problem solving and support (e.g. "*Have we got good examples of Ecosystems that we enable on an ongoing basis?*"). Only a relatively small proportion of liked (19%) and bookmarked (6%) messages dealt with topics that were not work-related (e.g. jokes and latest soccer news). Hence, the results of the qualitative text analysis substantiate our definition of key users which serves as a basis for the following analyses.

[1] http://cran.r-project.org/web/packages/igraph/index.html

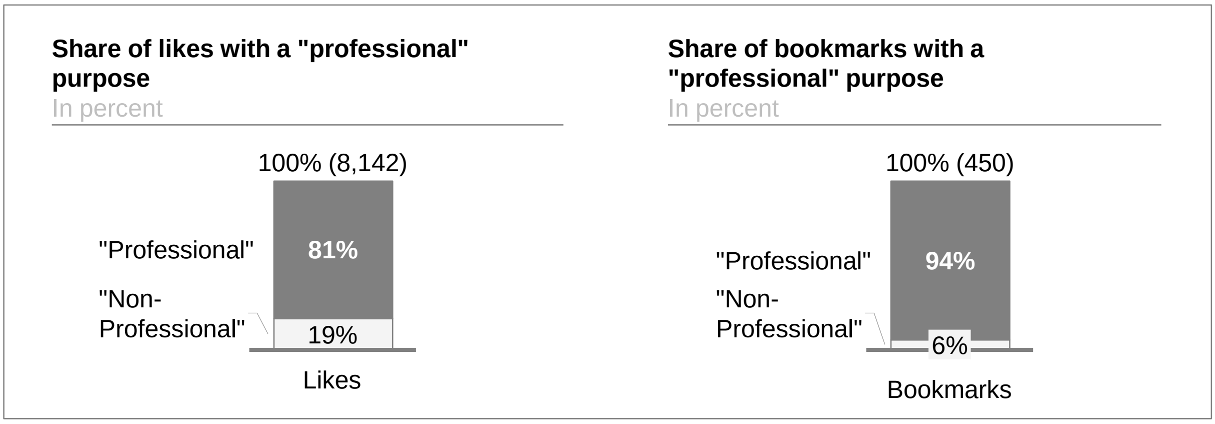

Figure 1. Share of likes and bookmarks with a professional purpose.

4.2 Results of the Social Network Analysis

As explained earlier, we define and identify key users as those users of the ESN whose messages received most likes and bookmarks (cf. Section 3.3). To get deeper insights into the characteristics of these key users, in a first step, we looked at whether the users whose messages received the most likes are also among the ones whose messages received the most bookmarks and vice versa. To do so, we derived two user rankings: first, we ranked the users with respect to their number of likes and their number of bookmarks, respectively. On this basis, we compared the top segments of both user rankings. For the top 1% segments of both rankings we observed a big overlap: 51% of the top 1% users with respect to the number of likes are also among the top 1% users with respect to the number of bookmarks. Only 25% of the top 1% users with respect to the likes are not among the top 5% users with respect to the bookmarks (cf. Figure 2).

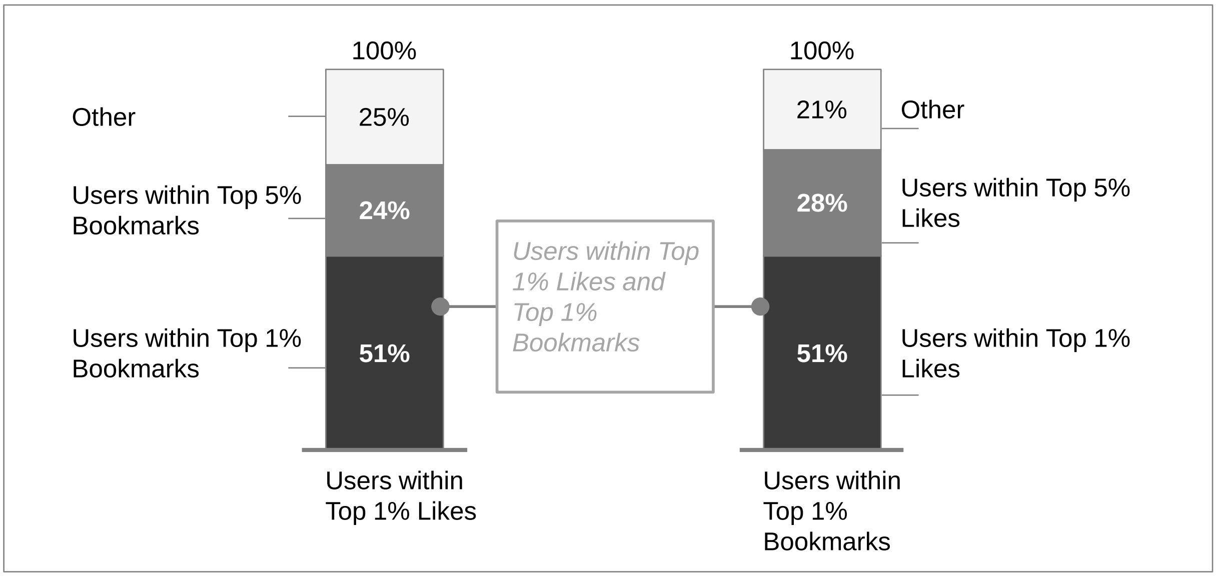

Figure 2. Overlap of users who received the most likes and bookmarks.

We conducted our analyses to identify the structural characteristics of key users for both users who received most likes and users who received most bookmarks. Due to the very similar results and the big overlap of users whose messages received the most likes and bookmarks, respectively, for this paper we decided to focus on the number of likes only (cf. page length restriction). Compared to analysing the number of bookmarks we expect the results to be more reliable: (1) our dataset contains much more likes (14,946) than bookmarks (599); (2) the number of users whose messages received at least one like (1,112) is much higher compared to those who received at least one bookmark (220); (3) in the context of ESN the like functionality seems much more common compared to the bookmark functionality. Hence, for the following analyses, we define and operationalise key users as those users of the ESN whose messages received the most likes (top 1% and top 5% segments).

To identify the structural characteristics of key users in ESN, we first investigate how key users are characterized with respect to their number of followers, written messages, and group memberships. We ranked the users for each of these characteristics and derived the top 1% and top 5% categories. The remaining users were classified as the “rest”. We then calculated the percentage of key users (top 1%, top 5%, and the “rest”) belonging to the respective category. Table 1 highlights that 51% of the top 1% key users are also among the top 1% users with the most followers; 93% of them are among the top 5% users with the most followers. Only 7% of the top 1% key users belong to the “rest”. Hence, we found that key users have a large number of followers. The results of our analysis regarding the number of written messages are as follows: All top 1% key users belong to the category of the top 5% users who wrote the largest number of messages; 65% of them even fall into the category of the top 1% message writers. Furthermore, key users are characterized by a quite large number of group memberships: 65% of the top 1% key users are among the top 5% users with the most group memberships.

Summing up the results of these analyses, it is evident that key users take an active part in ESN. Most of them belong to the top categories with respect to the number of followers, written messages, and group memberships. Thus the biggest overlap is observed for key users and those users who wrote the most messages, followed by those with the most followers and group memberships (cf. Table 1).

Key User	**Number of Followers**			**Number of Written Messages**			**Number of Group Memberships**		
Top	Top 1%	Top 5%	Rest	Top 1%	Top 5%	Rest	Top 1%	Top 5%	Rest
1%	51%	93%	7%	65%	100%	0%	28%	65%	35%
5%	15%	49%	51%	19%	65%	35%	11%	38%	62%
Rest	0%	3%	97%	0%	2%	98%	0%	3%	97%

Table 1. Overlap of key users and those users with the most followers, written messages, and group memberships.

In a second step, we analysed the key users’ centrality in the social graph (10,434 nodes and 137,550 directed edges) which is based on social links in terms of follower relations among the users. We applied in-degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality to the social graph. We then ranked the users for each centrality measure and classified them with respect to the categories top 1%, top 5%, and “rest”. Table 2 shows the percentage of key users (top 1%, top 5%, and “rest”) in the respective categories. Here, a user’s in-degree centrality corresponds to his or her number of followers (cf. also Table 1). However, the results in Table 2 do not only illustrate that key users are characterized by a large number of direct connections to other users (cf. in-degree centrality). Rather, the results for closeness centrality reveal that they are generally close to all other users in the network and therefore might be able to spread their contributions easily in the whole ESN (note that closeness centrality is based on a user's shortest paths to all other users in the network): 54% of the top 1% key users belong to the category of the top 1% users with respect to closeness centrality. The results for betweenness centrality and eigenvector centrality further underline that key users are very well connected in the social graph: 43% of the top 1% key users are among the top 1% users with the highest betweenness centrality; 48% of them among those with the highest eigenvector centrality.

Altogether, our analyses of the social graph show that many key users are among the best-connected users in the ESN. This holds for all centrality measures taken into account. However, in this context, it is remarkable that the biggest overlaps are observed for the key users and those users with the highest centrality with respect to the simple centrality measures in terms of closeness centrality and in-degree centrality. This is in keeping with Kiss and Bichler (2008) who derived similar results for the analysis of influence in customer networks.

Key User	**In-degree Centrality**			**Closeness Centrality**			**Betweenness Centrality**			**Eigenvector Centrality**		
Top	Top 1%	Top 5%	Rest	Top 1%	Top 5%	Rest	Top 1%	Top 5%	Rest	Top 1%	Top 5%	Rest
1%	51%	93%	7%	54%	80%	20%	43%	86%	14%	48%	91%	9%
5%	15%	49%	51%	16%	37%	63%	14%	40%	60%	14%	49%	51%
Rest	0%	3%	97%	0%	3%	97%	0%	3%	97%	0%	3%	97%

Table 2. Overlap of key users and those users with the highest centrality for each centrality measure applied to the social graph.

In a third step, we analysed key users' centrality in the activity graph (10,434 nodes and 9,645,500 directed edges) representing the users' communication activities in the form of directed links between senders and receivers of messages. In this context, we proceeded like we did for our analyses of the social graph. We applied in-degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality to the activity graph and classified the users with respect to their centrality for each centrality measure (top 1%, top 5%, and "rest"). Then, we calculated the percentage of key users in the respective categories. Our prior results (cf. Table 2 and the discussion above) have already shown that key users are characterized by a large number of written messages. The analysis of the activity graph highlights that key users are not only very active message writers, but are also among the users who receive the largest numbers of messages (cf. in-degree centrality): 45% of the top 1% key users belong to the top 1% category with respect to users' in-degree centrality. In addition, key users are strongly connected in the activity graph of the ESN with respect to closeness centrality: 53% of the top 1% key users are among the 1% users with the highest closeness centrality. Thus, their messages can reach a large number of users in a relatively short time. With respect to betweenness centrality, 57% of the top 1% key users fall into the category of the 1% users with the highest centrality. This means that key users are often included in the shortest paths between two other users in the network, may bridge structural holes in the network, and are therefore essential for a fast and effective exchange of information in the ESN. Finally, key users are also characterized by a rather high eigenvector centrality: 43% of the top 1% are among the top 1% users with the highest eigenvector centrality.

Summing up our analyses of the activity graph, we found that key users are not only involved in major parts of users' communication activities in the ESN (cf. number of messages written and received) but can also contribute to a fast and effective exchange of information due to their high (closeness and betweenness) centrality. As for the activity graph, the biggest overlaps with the key users are observed for centrality measures taking into account the shortest paths between users in the ESN (i.e. betweenness and closeness centrality).

Key User	**In-degree Centrality**			**Closeness Centrality**			**Betweenness Centrality**			**Eigenvector Centrality**		
Top	Top 1%	Top 5%	Rest	Top 1%	Top 5%	Rest	Top 1%	Top 5%	Rest	Top 1%	Top 5%	Rest
1%	45%	71%	11%	53%	87%	13%	57%	89%	29%	43%	73%	27%
5%	15%	39%	52%	18%	49%	51%	18%	48%	61%	14%	38%	62%
Rest	0%	3%	97%	0%	3%	97%	0%	3%	97%	0%	3%	97%

Table 3. Overlap of key users and those users with the highest centrality for each centrality measure applied to the activity graph.

In this subsection, we identified structural characteristics of key users in ESN by applying common centrality measures to the social graph and the activity graph of the ESN. The results underline that key users are generally well connected in terms of social links (cf. social graph) and communication activities (cf. activity graph) in the ESN. Comparing the results for both graphs (cf. Table 2 and Table 3), we found bigger overlaps of key users and the top categories for the centrality measures, if these were applied to the social graph. This holds for all centrality measures except for the betweenness centrality which leads to better results if it is applied to the activity graph.

5 Discussion, Limitations, and Future Research

In this section, we discuss how the findings of our analysis contribute to a better understanding of the role of key users in ESN, and look at implications of our research regarding both theory development and practical application. In addition, we also consider several limitations of our study as starting points for future research.

5.1 Discussion and implications for theory and practice

In this study, we primarily investigated the structural characteristics of key users in ESN. In doing so, we used data about the Yammer-provided functionalities to like and bookmark a message as indicators for its added value. We considered those users as value adding key users in the ESN whose messages received the largest number of likes (top 1% and top 5% segments). These users contribute and communicate their knowledge in the ESN thus helping other users to solve their daily problems and to get their professional work done more successfully and efficiently. By liking or bookmarking their messages, other users appreciate their help.

One theoretical contribution of our paper is that we brought together concepts from both Social Network Analysis and value based thinking. Prior studies focused mostly on mere social structures (e.g., Borgatti (2006)) without incorporating the value add of a user into their investigations. In that realm, a further contribution of our paper based on the Yammer dataset is that 81% of the likes and

94% of the bookmarks were attributed to messages that can be categorized as "professional". This high share of professional related content is all the more surprising as the organization's Yammer network was not organized by BIG's management, but rather arouses organically by employees. So far, although first studies have analysed parts of messages exchanged in their datasets (Richter and Riemer, 2013), it remained unclear whether "likes" and "bookmarks" reflected a practice to highlight professional content or were rather used to applaud private or social content, as it is the case with Facebook or Twitter (Naaman et al., 2010). To the best of our knowledge our study is the first to show how likes and bookmarks can be applied as indicators for the added value of a message. This result is of special interest for practitioners as they often hesitate to push ESN in their companies because of the fear that the content of communication is not work related. In addition, practitioners may use the number of likes in ESN as an indicator to identify knowledge support hubs. The sum of these hubs can be seen as an informal service helpline for employees where people help other people with their knowledge to solve their daily problems. This becomes especially important in an increasing dynamic work environment where employees more often change their jobs and work at distributed places. Thus, the role of ESN can be seen as "support information systems".

These results serve as a prerequisite for our further analysis allowing us to investigate the structural characteristics of the group of the top 1% (top 5%) key users who received more likes than 99% (95%) of all registered users. Our analysis showed that, first, key users are characterized by a high number of written messages, a large number of followers and group memberships (in this ranking order). Thus, this group plays an active part in ESN. Second, the top 1% key users are well connected with respect to different centrality measures both in the social as well as in the activity graph. Structurally, in our context, key users have a central position in the network (Iacobucci, 1996). As regards practitioners, this means that key users (knowledge hubs) can help for example to effectively distribute information in an ESN (as they are characterized by short paths to the other users resulting in a high closeness centrality). In addition, they can for instance contribute to bridging structural holes (Burt, 1992) between sub-networks in the ESN which do not or only little overlap (as they are often positioned on the shortest path between two other users resulting in a high betweenness centrality). Hence, key users can enable a more effective and rapid exchange of information between different working groups which are only sparsely connected, for example. More generally speaking, if key users (knowledge hubs) have a central position in the ESN, they are crucial for the diffusion of innovative ideas which essentially depends on how people are connected and influence each other (Ciriello et al., 2013). That could also be important in large enterprise transformation programs where targeted internal communication strategies are needed in order to disseminate information across the entire company within a short timeframe. Furthermore, the insight that key users are well connected could also be used for example in cases where companies do not have the "like feature" in their internal enterprise communication systems but aim to identify those people who act as an informal service helpline for other employees.

Regarding methodology, our results have implications for the application of Social Network Analysis, too. First of all, our findings show that the social graph is at least as appropriate to characterize key users as the activity graph. This is surprising, because prior studies have argued that the activity graph leads to better results (Heidemann et al., 2010; Xu et al., 2008; Chun et al., 2008). Against the background that analysing the activity graph yields a considerably higher effort because of a much higher number of ties (which may be important in practice), we recommend a thoughtful choice when deciding for or against using the activity graph. Alongside with this, it was even more surprising to see that simple centrality measures like in-degree centrality proved to be more beneficial than complex measures like eigenvector centrality. While the scientific community has constantly been discussing new, more complex measures (Heidemann et al., 2010; Lu et al., 2012), we would like to state that in this case simple centrality measures outperform more complex measures and are easier to be implemented in practice.

5.2 Limitations and further research directions

Our research provides first insights into this interesting field. However, there are several limitations which can serve as starting points for future research. First, we only considered one single company which provided us with the relevant data needed to conduct this research. Nevertheless, the ESN of this multinational consulting company was intensively used by a large number of users from all over the world. Thus, we assume that our results also hold for other companies using (other) ESN or similar communication systems. Second, for our data analyses, we defined and operationalised key users as those users of the ESN whose messages received the highest number of likes. Obviously, likes cannot completely reflect the concrete effect and the value add of a message or a user for the company. However, the qualitative text analysis conducted for 8,142 messages indicates that 81% of the messages which received likes are work-related. Hence, it may well be assumed that these messages contribute relevant knowledge helping to get professional work done more successfully and efficiently. While in a first step it seems appropriate to use likes to operationalize the value add for the company, further studies are needed to analyse this aspect in-depth (i.e. how can value add be measured in ESN?). Finally, we did not consider all aspects of the social connections and communication activities of the key users in our analysis of the social graph and the activity graph of the ESN. Nevertheless, we applied the most common centrality measures to both of these graphs. Hence, profound statements about the key users' centrality could be made, but future research is needed to analyse key users' inter-relationships (e.g. are the key users (strongly) connected among themselves?). In this context, graphical analyses (e.g. with Social Network Analysis tools like Commetrix) or cluster analyses based on the social graph and the activity graph seem to be promising starting points to get deeper insights into the structural characteristics of value adding users. In the course of this development it would also be of interest to incorporate further characteristics of key users beyond the social embeddedness (e.g., demographics, position in the organization, and hierarchies) in order to get a comprehensive picture of value adding key users.

6 Conclusion

Ever more organizations are adopting ESN as a means to facilitate collaboration, communication, and knowledge sharing between their employees within and across organizational boundaries (Faraj et al., 2011; von Krogh, 2012). An important aspect of understanding the phenomenon ESN is to identify and characterise those users who contribute and communicate their knowledge in the ESN and help other users to get their daily work done. Despite emerging scientific work in the field of ESN, the role and behaviour of these value adding users in view of knowledge-intensive corporate work is still not fully understood. Thus, the aim of this paper was to investigate the structural characteristics of value adding key users in the context of ESN and to characterize these users. Our analysis is enabled because a plethora of data are generated in ESN when users exchange and connect with others (Giles, 2012). This data wealth allows for unprecedented opportunities to analyse and understand value adding key users in ESN. Against this background, we analysed a large scale dataset of a global consulting company using the ESN Yammer.com. First, using qualitative text analysis and Social Network Analysis, we found that 81% of the likes and 94% of the bookmarks were attributed to messages that can be categorized as "professional". This result has to be seen in the light that the Yammer network was not organized by BIG's management, but rather arouses organically by employees. Second, we could show that key users, defined as users whose messages received the highest number of likes (top 1% and top 5% segments), are characterized by a high number of written messages, a large number of followers, and also a remarkable number of group memberships. Third, our analysis indicates that key users are well connected both in the social and in the activity graph giving them, from a structural perspective, a central position in the ESN. In sum, from a practical perspective, ESN can be seen as an informal service helpline for employees where people help other people with their knowledge to solve their daily problems. This generates value for the entire firm.

In addition to these results, with respect to theory, we could show that, contrary to prior studies, the social graph is at least as appropriate to characterize key users as the activity graph, and that simple centrality measures like in-degree centrality have proved to be more beneficial than complex measures (like eigenvector centrality). With these results, we hope to contribute to a better understanding of ESN. Summing up, we believe that our study is a first but indispensable step with regard to studying value adding key users in ESN. In future research, we need to come to a much clearer understanding of how these users act, communicate, and connect with others. We hope that our present results will stimulate further research on that fascinating topic and support practitioners to better understand and use ESN.

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