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Evolution, Structure and Users' Attachment Behavior in Enterprise Social Networks

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Abstract

Due to the increasing number of organizations who have started to implement Enterprise Social Networks (ESN), their network structure, which is invoked by the users and interactions among them, has gained increasing attention, both by practitioners and researchers. However, prior research has not considered how the network structure of ESN evolves over time through interactions among users. To address this lack in research we investigated two research questions: 1) How do the topological characteristics of ESN evolve in time? 2) How is users' attachment behavior characterized with respect to the creation of social relationships during the evolution of ESN? Drawing on a rich dataset comprising more than 4 years of networking and interactions, we are able to show that ESN do not evolve randomly but follow preferential attachment. Rather, our findings indicate a significant, positive correlation between users' centrality in the network and their number of new social relationships.

In the last couple of years, more and more companies have started to implement so called Enterprise Social Networks (ESN) to foster collaboration, communication, and knowledge-sharing among employees [8, 55]. According to a study by Deloitte [23], more than 90% of all Fortune 500 companies had used ESN by the end of 2013. Due to the growing importance of ESN and its use in daily work practices of employees, there is an increasing demand to better understand the role and impact of these social technologies in and on knowledge-intensive corporate work [14, 48]. First studies have shown that ESN can, for instance, support expert finding, information seeking, idea sharing, or team coordination [24, 51]. ESN can be defined as web-based platforms, which offer employees new ways of communication and collaboration in both public enterprise-wide communication streams and private groups with restricted memberships [49]. ESN allow users to contribute content to a shared pool, allow profile information to be presented, and connects users through features like 'friend requests' [12].

Prior studies have shown [e.g., 31, 56] that the structure of ESN is of great importance. On the one hand, the network structure of ESN plays a decisive role for the explanation of user behavior [56]. On the other hand, topological characteristics like transitivity and mutuality are significant predictors of the desire to form new ties [31]. As the network structure of an ESN is invoked by the connections among its users, it changes in time as more employees are participating and creating new links. Social networks in general and ESN in particular are typical examples of dynamic networks which evolve with respect to a growing number of users and interactions among them [30]. With our research on the evolution of ESN, we aimed to investigate patterns in users' networking behavior and interaction in the ESN that lead to a dynamic network structure. Accordingly to studies with a similar research focus for social media networks [cf. e.g., 30, 40], we did not consider how the platform emerges in the organization and how it is adopted by the employees (for information on the emergence of ESN see [50]).

Especially for organizations that plan to implement an ESN it seems important to gain indications of how the users connect and interact in the ESN. These insights in the dynamic of the structure allow, for instance, to support the avoidance of isolated subnets. Rather, knowledge of the patterns in users' attachment behavior might be helpful with respect to the identification of potential future key users [cf. e.g., 13], since users' importance is inferred by their structural position in the network [36].

In this context, the structure and evolution of many real world networks [e.g., 38, 46] have been studied before. To explain and illustrate their dynamics, models for the evolution of networks have been proposed. These models can be found for a large variety of real world networks such as communication networks, information networks, and social networks [22, 38]. First network evolution models for social media networks can be found as well [e.g., 41, 30] due

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to the growing popularity and importance of social media. However, it is unclear, if these models can be applied to ESN. Whereas ESN are available to employees of an organization only and are mainly thought to support communication and collaboration [49], social media networks are available for the mass and differ in their main focus [see 39]. Rather, ESN differ from other social media networks with respect to some of their topological characteristics [cf. 18].

Today, there is still a lack of research on the evolution of ESN (i.e., how does the network structure change in time). In this paper, we aim to address this issue. Based on a dataset of an ESN used by the German Armed Forces (Deutsche Bundeswehr), we investigate how the topological characteristics evolve in time. In a second step, we analyze users' attachment behavior to other users, i.e., the creation of new social relationships, with respect to these users' position in the network. Therefore, we address the following research questions:

1) How do the topological characteristics of ESN evolve in time?

2) How is users' attachment behavior characterized with respect to the creation of social relationships during the evolution of ESN?

Our results indicate that the structure of ESN does not evolve randomly, but follows preferential attachment due to its power-law degree distribution. Rather, we are able to illustrate that new users (i.e., users who join the ESN in the current period) mainly attach to users who have joined the ESN in prior periods. In addition, we found that a user's position in the social graph influences his or her attractiveness of creating social relationships to other users. Whereas many organizations hesitate to introduce ESN for the fear of failure to support active networking and interaction among all employees to benefit from the positive effects of the ESN, our results may help them, since they contribute to a better understanding of the dynamics in the creation of social relationships in ESN. Given that social technologies like ESN are a core phenomenon of the 21st century, our findings contribute to a more refined understanding of ESN in general.

The remainder of this paper is structured as follows: In Section 2, we give an overview of the theoretical background of our research. In Section 3, we describe the case setting as well as the data collection and preparation process, followed by a short introduction of measures and methods used during our analysis. Our findings are presented in Section 5. Finally, in Section 6, we critically discuss implications and limitations of our research and provide directions for further research. We conclude with a brief summary.

2. Theoretical background

This section is dedicated to a brief overview on the theoretical foundations of our research. We elaborate on the structure of ESN and how it can be quantified. We furthermore show how network evolution has been analyzed in general and for social media networks in particular.

2.1 Enterprise Social Networks and their structure

Prior research has shown that the network structure of ESN play a decisive role in understanding and explaining user behaviour in ESN [56]. Here, for example, Golder and Yardi [31] found that the topological characteristics transitivity and mutuality are significant predictors of the desire to form new ties. The structure of an ESN is invoked by the binary connections among users. It 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 (…)" [17, p. 922]. 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., 2, 10, 32]. A well-known method to analyse the network structure is Social Network Analysis (SNA) [57] that can form the theoretical basis for understanding the network structure of social networks in general and ESN in particular.

SNA offers both measures with respect to the topological characteristics of a network represented as a graph and measures that quantify the position of a user in the network by means of user centrality [16, 57]. Most common topological characteristics are, for instance, the global clustering coefficient, shortest average path distance, and density as well as the graph's degree distribution [5, 30, 57]. These characteristics were, amongst others, studied for a variety of social media networks [e.g., 4, 27, 45, 54]. The first research on the topological characteristics on ESN was conducted by Chelmis and Prasanna [18], who studied the network structure using the activity graph of an ESN called @replies. They found that for some topological characteristics, like small world characteristics, ESN differ from social media networks. However, they did not consider network evolution.

Next to the characteristics of the graph, the structural characteristics of the single users can be measured. Here, a well-known method is node centrality [57]. The most common centrality measures include degree centrality, closeness centrality, and betweenness centrality [28]. In the context of social media networks in general and ESN in particular, there are first articles using these centrality measures to identify influential users, for example to foster more effective advertising or marketing strategies [e.g., 32, 33, 53] or to characterize central users on academic networking platform [34] and value adding users in ESN [12].

To sum up, researchers have emphasized the importance of the network structure and central nodes. But, to the best of our knowledge, research lacks on considering both the structure of an ESN and its evolution. Therefore, the aim of our paper is to investigate how the topological characteristics change in time and how users' centrality influences the creation of new social relationships.

2.2 Evolution of networks

Many real-world systems take the form of networks, as they can be represented by a set of nodes connected by a set of edges. Popular examples are, for instance, the World Wide Web (WWW) or social networks [38]. Some of these networks are static, for example blood vessels. Others, like social networks, are dynamic since their structure changes in time [11, 38]. However, in recent years, this topic has been subject to an increasing amount of attention [cf. e.g., 5]. Whereas the evolution of networks has initially been thought to be random [25, 26], research found increasing evidence for a number of non-random characteristics [15]. Many real world networks obey unexpected scaling laws [6, 11] and differ from randomness [37].

Hence, there has been research resulting in models that treat networks as evolving dynamical systems. In prior research, models have been proposed [e.g., 10, 30, 38] being able to capture and reproduce properties observed on various kinds of real world networks [7]. Most of these models consider 1) a continual addition of new nodes and links and 2) preferential attachment that is mostly to nodes that have a high degree centrality (i.e., lots of ties to other nodes) [31]. One of the best-known and most applied preferential attachment models was proposed by Barabasi and Albert [11] (also known as BA model), who used node's degree centrality as driver for the creation of new links. Initially, it was applied to the WWW [11], but later the BA model was also adapted for other kinds of networks [e.g., 40]. Other models consider the nodes' heterogeneity as the main predictor for attachment of new nodes [15] or focus on triadic closure [58].

First network evolution models for different social media networks can be found as well [e.g., 30, 41, 42]. Among the most studied networks are Twitter [e.g., 30] and Flickr [41, 42, 44]. The models mainly differ in the considered driver for preferential attachment behavior. Kumar et al. [41], for instance, found preferential attachment biased by the cost of creating a connection to an isolated community and the ease of connecting with a large single component, while Leskovec et al. [42] stated that users create links with users they have already been close to before. Other drivers that were observed are triadic closure [e.g., 44] and degree centrality with a cut-off (i.e., restriction on degree centrality) [30]. While all the previous studies considered logical time steps [30], Gaito et al. [29] investigated bursts in users' creation of links.

Although the BA model is among the most applied models for network evolution and first models on OSN use degree centrality as driver for the attachment process [e.g., 30], some authors question its applicability on social networks [38, 47]. However, the use of other measures was proposed. Abbasi et al. [1], for instance, suggested betweenness centrality. In this paper, we aim to address the evolution of the structure of ESN and to analyze the drivers for users' attachment behavior due to the lack of research on this theme.

3. Research method

In this section, we provide an overview of the setting of the case and the data collection. Then, we discuss the analysis process and the applied methods.

3.1 Setting

We use the case of the medical service of the German Armed Forces to gain first insights into the evolution of ESN. The medical service employs amongst others nearly 3,000 medical officers and 1,600 trainee medical officers who are distributed among five major military hospitals, 37 public universities that offer medical studies, and 200 other facilities. In 2010, the German Armed Forces started to implement an ESN for its medical service employees – in the following referred to as Med-Net. The main goals of Med-Net were described as (1) fostering knowledge transfer and collaboration, (2) improving the quality of education and the in-service training of new employees, and (3) creating a collaborative knowledge base. In the ESN, all users are represented by a user profile. After joining the network, the users can send contact requests, which have to be confirmed, or write direct messages. The case of Med-Net was selected because of the large dataset including information on users and links (i.e., social links and activity links) from Med-Net's launch in 2010 till February 2015. Timestamps for users' accession date and the creation of links among the users allow us to analyze the evolution of the ESN.

3.2 Data collection and preparation

We were provided with the dataset ranging from November 2010 to February 2015. To investigate the evolution of Med-Net, we aggregated the data on a quarterly basis. Whereas, the ESN was only available to a very small number of users as part of a testing phase in the months after its launch, our analysis were not conducted for earlier times than 2nd quarter 2011. The dataset was provided in MS Excel format, and to ensure confidentiality, all personal information (e.g., user names and the messages' content) was removed during data export.

In the following, we provide a few descriptive statistics on our dataset. The dataset contains information about 2,826 unique users as well as the month and year they have joined Med-Net. 1,645 of the users have at least one confirmed contact request ("social relationship") to another user (total number of social relationships: 7,390). Moreover, the data include 18,418 direct messages written by a total of 830 users. In Med-Net, the number of users and social relationships increased steadily. Hence, in 2nd quarter of 2011, 142 users were part of the ESN, but in the 1st quarter of 2015, the ESN was used by 2,826 users. This means an average annual growth rate of nearly 21%. In addition, Med-Net shows a continual addition of social relationships (average annual growth 23%) and messages (average annual growth 37%). Altogether more than 70% of all users can be considered as active users of the ESN, because they are involved in the communication activity or social networking.

4. Data analysis

To investigate the evolution of ESN we calculated topological characteristics of the social graph of the ESN and applied the most common centrality measures to the social graph (i.e., social relationship) and the activity graph (i.e., communication activity in terms of messages exchanged among the users).

A network and its structure can be described using topological characteristics. Some of the most common measures are degree distribution, global clustering coefficient, density, and small world characteristics in terms of the average shortest path [46, 57]. Degree distribution $P(k)$ measures the fraction of nodes having degree k. In the context of Med-Net k represents the number of a user's social relationships. The degree distribution of social networks and social media networks is often found to show power-law characteristics (i.e., broad distribution with a heavy tail) [30]. Thus, there are a large number of users having a small number of social relationships and a small number of users having many social relationships. To investigate whether Med-Net shows such characteristics, we fitted a power-law degree distribution [cf. 20] and tested its suitability by using a Kolmogorov-Smirnov test [35]. We further considered the global clustering coefficient C, which can be described as the ratio of three times the number of closed triples to the number of connected triples in the network [46]. A connected triple is a set of three nodes sharing at least two edges while a closed triple shares at least three edges. In the context of Med-Net, a high clustering coefficient indicates that users are more likely to create a social relationship with users they have mutual social contacts with. Moreover, we also calculated the network density, which describes the portion of potential ties that actually can be found [30]. Another well-known topological characteristic is the average shortest path, which is quantified by the average geodesic distance between any pair of nodes in the network [46]. Prior studies [e.g., 43] have found it to be small even for very large networks in general and also for social media networks in particular [9]. The calculation of these topological characteristics for the social graph of the ESN for each quarter respectively allows us to analyze how the structure evolves over time. Moreover, we are able to compare its evolvement with dynamics known for other real world networks.

Finally, this analysis are also a prerequisite for the investigation of users' attachment behavior which leads to the observed network structure of the ESN. To investigate the attachment behavior of users in the ESN, we applied the most common centrality measures, degree centrality, closeness centrality, and betweenness centrality [28] to each node in the social graph and activity graph of the ESN. This analysis was conducted for each of the observed periods. In a next step, we used the results as a basis to investigate drivers in users' attachment behavior. Therefore, we used Spearman rank correlation [51] and measured the correlations between users' centrality and the number of new contact requests in the next quarter. Altogether, the results of the correlation analysis allow us to get first and interesting insights in the patterns in users' attachment behavior. In addition, they allow conclusions about the role of central users for fostering networking and interaction among the users (e.g., how are they characterized with respect to their structural position in the network?)

5. Findings

This section is dedicated to the results of our study. First, we focus on the topological characteristics of the

ESN's social graph. The second part concentrates on the analysis of users' attachment behavior and potential drivers for preferential attachment of social relationships.

5.1 Topological characteristics

In a first step, we analyzed the topological characteristics of the social graph of the ESN, which is based on social relationships. We calculated the global clustering coefficient, the average shortest path length, and the density for each quarter. Due to the closed testing phase, our analysis started with 2nd quarter 2011.

The results indicate that the ESN is characterized by a low global clustering coefficient. While in 2nd quarter 2011 the clustering coefficient was 0.32, it decreased over time and was 0.17 in 1st quarter 2015. The average quarterly decrease of the clustering coefficient is about 4%. Our results further indicate that the ESN is getting less dense over time. In 2nd quarter of 2011, we observed a density of 0.03, but in 1st quarter 2015, the density was 0.002. This results in an average decrease of 15% per quarter. Moreover, our analysis indicates that the average shortest path length increased in time. Med-Net had an average shortest path length of 3.1 in the 2nd quarter of 2011, and of 3.8 in 1st quarter 2015. Finally, our analysis showed that for all observed quarters, nearly all users with at least one social relationship are connected in a large single-component.

In a second step, we analyzed the degree distribution $P(k)$ of the social graph of Med-Net for each quarter. A power-law distribution was fitted for each quarter to analyze if the distribution shows power-law characteristics. The liability of the fitted distributions was tested using a Kolmogorov-Smirnov test [35]. For each quarter, a continuous power-law distribution could be fitted with values for the exponent α between 1.72 and 2.67. The values for k_{min} (i.e., the smallest value of k the distribution was fitted for) are nearly 0. This indicates that the fitted power-law distributions are suitable for all values $k \geq 1$. Hence, the distributions were fitted for all nodes with at least one confirmed social relationship. The p-values of the Kolmogorov-Smirnov test are nearly 1 for all distributions. Hence, we can assume that the degree distribution of the ESN is power-law.

Altogether we found that the structure of the ESN can be considered as dynamic, as the topological characteristics change in time. Although the ESN mainly consisted of a large single component, this component seems to get less dense in time. Moreover, the already low clustering coefficient decreases which indicates that friends are not very likely to share mutual social relationships. In addition, the power-law degree distribution indicates that the networks evolvement is not random, but follows preferential attachment.

5.2 Attachment behavior of users

Whereas our previous analysis showed that the evolution of ESN follows a preferential attachment, we wanted to investigate potential drivers. Hence, in a further step, we analyzed the attachment behavior of users. For our analysis, we partly followed Abbasi et al. [1] who analyzed the attachment behavior in a co-authorship network of publications. In a first step, we investigated the attachment behavior of new and existing users in each quarter. Existing users are defined as those users of the ESN who already have joined the network at least one quarter ago, while a new user is defined as a user who joined the network in the current quarter. Table 1 shows the results. For each quarter it includes the number of existing users as well as the number of new users. Further, the table contains the total number and share of new users who created at least one new social relationship to a new or an existing user, respectively. This analysis was also conducted for old users. For example, in 2nd quarter 2012, 91 new users joined the ESN and 7 (8%) of them created a social relationship to at least one other new user, and 26 (29%) of them created a social relationship to at least one of the 880 users who had joined the ESN previously. In the same quarter, 32 (4%) existing users built a social relationship with at least one new user and 102 (12%) with at least one other old user. These results indicate that except for year 2011, only a small share of the new users created social relationships to another new user. Instead new users tended to befriend existing users. Inverted attachment behaviors can be observed in the 3rd quarter or 4th quarter of the sole years. In these quarters new users are more likely to connect with other new users than with existing users. Similar results are yielded when investigating the attachment behavior of existing users. Here, the share of existing users who created at least one social relationship to other existing users is higher than the share of existing users who created a social relationship to at least one new user. In 4th quarter 2013, for instance, 47 (3%) existing users created at least one new social relationship to a new user and 158 (10%) of them to an existing user. Moreover, we found that the share of users who created a social relationship decreased in time.

Table 1. Creation of social relationships between users in Med-Net

Quarter	No. of users	No. of new users	No. of new users creating at least one social relationship to a new user		No. of new users creating at least one social relationship to an existing user		No. of existing users creating a least one social relationship to a new user		No. of existing users creating a least one social relationship to an existing use	
2nd Quarter 2011	142	138	64	(46%)	13	(9%)	2	(50%)	1	(25%
3rd Quarter 2011	472	330	86	(26%)	84	(25%)	49	(35%)	81	(57%
4th Quarter 2011	775	303	54	(18%)	78	(26%)	58	(12%)	150	(32%
1st Quarter 2012	880	105	2	(2%)	17	(16%)	26	(3%)	106	(14%
2nd Quarter 2012	971	91	7	(8%)	26	(29%)	32	(4%)	102	(12%
3rd Quarter 2012	1025	54	4	(7%)	8	(15%)	27	(3%)	71	(7%
4th Quarter 2012	1170	145	14	(10%)	27	(19%)	37	(4%)	137	(13%
1st Quarter 2013	1302	132	5	(4%)	19	(14%)	28	(2%)	116	(10%
2nd Quarter 2013	1376	74	3	(4%)	20	(27%)	27	(2%)	105	(8%
3rd Quarter 2013	1544	168	8	(5%)	27	(16%)	24	(2%)	104	(8%
4th Quarter 2013	1726	182	16	(9%)	36	(20%)	47	(3%)	158	(10%
1st Quarter 2014	1988	262	9	(3%)	22	(8%)	34	(2%)	153	(9%
2nd Quarter 2014	2103	115	3	(3%)	15	(13%)	19	(1%)	107	(5%
3rd Quarter 2014	2510	407	42	(10%)	1	(5%	1	(1%	12	(6%
4th Quarter 2014	2713	203	3	(1%)	19	(9%	1	(1%	14	(6%
1st Quarter 2015	2826	113	1	(1%)	11	(10%	1	(0%	4	(2%

While in 4th quarter 2011, 18% of all new users created at least one social relationship to a new user and 26% of them to at least one existing user, in 4th quarter 2014 only 1% created a relationship to at least one new user and only 9% to at least one old user.

Summing up the results, only a minority of the new and the old users created new social relationships. Especially in later quarters, there seems to be a group of users who are responsible for the creation of social relationships. With respect to users' attachment behavior, we found that both new users and existing users tend to create social relationships to existing users, while only a small number of users create social relationships to users who have joined the ESN in the current quarter. Moreover, the preference of social relationships to existing users appears to be responsible for the existence of the large single component. The inverted attachment behavior of new users in some quarters might be due to new trainee medical officers joining the medical service unit mostly in September (3rd quarter) and October (4th quarter). Initially, these new members are mainly in contact among themselves. Therefore, they connect primarily with each other in the ESN.

In a second step, we aimed to investigate potential drivers for preferential attachment. Hence, we analyzed how a user's position in the network and his or her communication activity influences the attachment behavior of other users. Therefore, we do not only focus on a user's degree centrality in the social graph and in the activity graph of the ESN, but also calculated closeness centrality and betweenness centrality for the social graph as well as the activity graph of the ESN. We used Spearman rank correlation to measure the correlation between existing users' centrality and the number of users who attach to them in the following quarter. For instance, we look at the correlation of a user's centrality in 1st quarter 2014 and the number of contact requests he or she received and confirmed in 2nd quarter 2014. The results of our analysis are presented in Table 2. The significance of the results was tested by the use of a 2-tailed t-test [21]. All results were found to be significant at the 0.01 level.

The results in Table 2 indicate that users' attachment behavior is positively correlated to user centrality. Hence, users tended to attach to well-connected users of the social graph as well as the activity graph. Table 2 also shows that a user's activity (centrality in the activity graph) seems not as important as his or her social relationships. Here, users tended to create social relationships to users who already had a large number of friends (i.e., degree centrality) or are close to all other users in the network (i.e., closeness centrality). In addition, the most attractive users are also able to control information flows (i.e., betweennness centrality) in terms of their position in the social graph. This holds for all quarters that were analyzed.

Altogether we found that users' degree centrality in the social graph seems to be the best predictor of preferential attachment for new social relationships in the ESN. The results further indicate that also closeness centrality and betweenness centrality in the social graph can be seen as drivers for preferential attachment, while users who take part in the most part of the ESN's communication (cf. out-degree centrality) and who control communication flows (cf. betweenness centrality in the activity graph) seem not to be preferred for the creation of a social relationships.

Table 2. Correlation between users' centrality and new contact requests in each quarter

Quarter (Q)	Social Graph C_D	C_C	C_B	Activity Graph C_{Out-D}	C_C	C_B
2nd Q 2011	0.58	0.51	0.50	0.26	0.30	0.28
3rd Q 2011	0.43	0.40	0.41	0.16	0.12	0.22
4th Q 2011	0.32	0.30	0.31	0.21	0.20	0.17
1st Q 2012	0.40	0.41	0.41	0.23	0.22	0.28
2nd Q 2012	0.26	0.25	0.23	0.18	0.17	0.19
3rd Q 2012	0.38	0.37	0.38	0.28	0.29	0.27
4th Q 2012	0.44	0.44	0.55	0.36	0.37	0.31
1st Q 2013	0.37	0.37	0.34	0.25	0.28	0.23
2nd Q 2013	0.36	0.33	0.34	0.25	0.28	0.26
3rd Q 2013	0.23	0.21	0.23	0.18	0.17	0.19
4th Q 2013	0.15	0.12	0.15	0.11	0.12	0.11
1st Q 2014	0.20	0.16	0.19	0.12	0.06	0.10
2nd Q 2014	0.20	0.17	0.19	0.15	0.17	0.18
3rd Q 2014	0.39	0.38	0.48	0.09	0.06	0.11
4th Q 2014	0.29	0.22	0.30	0.11	0.07	0.12

All correlations are significant at the 0.01 level
C_D: Degree Centrality
C_C: Closeness Centrality
C_B: Betweenness Centrality
C_{Out-D}: Out-degree Centrality

6. Discussion and conclusion

In this section, we discuss the contribution of our research and its implications for theory and practice. We also consider the limitations of our study as starting points for future research. Finally, we will conclude with a short summary of our research.

6.1 Implications for research and practice

In this study, we investigated the evolution of the network structure of ESN. In doing so, we considered how topological characteristics change in time and how the users behave with respect to the attachment process for the creation of new social relationships. First, in our paper, we considered the structure of an ESN as well as the aspect of time. Prior studies mostly focused on the investigation of topological characteristics of the graph [e.g., 18] or the structural characteristics of the single users [e.g., 13], without investigating the dynamics in their structure. In this context, we found that the evolution of the ESN led to a single giant component containing nearly all users with at least on social relationship. With respect to the decreasing density and low clustering coefficient, we found that there must be a small group of users connecting the users in the ESN. This result is of special interest for practitioners for two reasons. 1) It shows that networking and interaction in the ESN are not subject to local boundaries within the organization. Rather, they help to connect employees with various characteristics, like different locations. 2) These connective users are of special interest with respect to supporting and governing networking and interaction in terms of communication and collaboration in the ESN.

Second, our results indicate that the formation of the social graph in ESN is not random. Rather; we observed a power-law degree distribution. This result is of special interest since studies [e.g., 53] found that not all social media networks exhibit power-law degree distributions. The power-law degree distribution further indicates the existence of preferential attachment. We found that new users tend to befriend existing users instead of other new users. In contrast, the attachment of the new users to the single giant component of the graph is mainly radiated from the existing users. Hence, most users with at least one social relationship are interested in being part of the community. Therefore, they take an active part in the networking process. Moreover, practitioners need not hesitate that the ESN consists of just sparely connected components. Indeed, the structure of the ESN, which depends on how users are connected, allows an easy diffusion of news and ideas [19]. This is of great relevance when information has to be disseminated across the entire organization in a short time.

Third, alongside with this, we were also able to show that users' position in the network influences the attachment behavior. We found that users tend to attach central users in the ESN' social graph and activity graph. More detailed, users create social relationships with users that already have many friends (cf. degree centrality in the social graph). We observed the so-called rich-get-richer phenomenon [59]. Thus, from a practical perspective, organizations do not have to constantly identify key users [e.g., 13], since users with a central position in the ESN are very likely to keep it. For practitioners, it is important to involve these users in fostering networking and interaction in the ESN. This might ensure that all users are connected in relative short time, after joining the network.

6.2 Limitations and future research directions

Although our study is the first one to consider the structure of an ESN and its evolution and the results of our analyses provide interesting insights, there are several limitations which can serve as starting points for future research. First, we only considered one single organization, which provided us with the relevant data needed to conduct this research. Nevertheless, the ESN of the German Armed Forces has a large number of users. Thus, we assume that our results may also hold for other organizations using ESN. Second, we focused on the creation of social relationships only. However, it may well be assumed that also the creation of activity links (i.e., messages) is an important part of the ESN's evolution. While in a first step it seemed appropriate to focus on social relationships, further studies are needed to analyze the role of user activity for network evolution in-depth (e.g.,. does the evolution of the social graph differ from the activity graph?). Third, military organizations might differ from business organizations in some points. But according to the work descriptions in the *Administrative Order on the Position of the Military Superior* [3] military ranks can be seen as equivalent to formal job titles in organizations like upper, middle and lower management. Hence, we do not think that ESN in non-military organizations evolve different. Fourth, we considered only a selection of potential aspects and drivers for the creation of social relationships in ESN. Nevertheless, we considered both a user's centrality in the social graph and in the activity graph as potential drivers of preferential attachment. However, further research is needed to analyze more aspects of preferential attachment (e.g., need to consider a fitness parameter like, for instance, users' role in the organization's hierarchy?). In addition, we believe that also a user's offline social network (i.e., colleagues and friends) might affect his or her attachment behavior. Finally, our research approach is mostly exploratory and data driven. Nevertheless, we were able to gain first and interesting insights on this topic which can be used as a basis for further research. Based on further in-depth insights in the dynamics and evolution of ESN, we aim to propose a model for the evolution of ESN in the future.

6.3 Conclusion

There is a growing body of literature in the emerging field of ESN, as more and more organizations have started to use ESN, for example, to foster collaboration and communication among their employees [8, 55]. However, we still observe a lack of research focusing on the evolution in the structure of these networks. The dynamic was not considered in prior studies on the structure of ESN [e.g., 12, 13], and even less research was conducted with respect to the topological characteristics of the social graph of ESN (for research on the activity graph see [18]). Thus, with this paper, we aimed at analyzing how the characteristics that describe how the structure of an ESN evolve in time as well as at identifying drivers in users' attachment behavior. Our analysis was enabled by the use of a large-scale dataset of the German Armed Forces. This dataset contains all information regarding the addition of users and links from over a long period of time since the implementation of the ESN. By calculating the most common topological characteristics, we were able to show how ESN are in some aspects comparable to other real world networks and in particular social media networks, but also differ in terms of their clustering coefficient. Rather, the attachment of new links is not random, but significantly and positively correlates with users' centrality in the social graph.

With our paper we hope to contribute to a better understanding of the emerging phenomenon ESN. We believe that our research is a first but interesting step towards understanding the evolution of the structure of ESN and its drivers. We also hope that our paper will stimulate further research on this interesting topic and will be used as a starting point for further research. In addition, it will contribute to a better understanding on the structure of ESN and help organizations to support and govern networking and interaction in terms of communication and collaboration in the ESN.

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8. References

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