Business Intelligence 2.0

Sebastian Behrendt and Alexander Richter

Abstract The increasing use of enterprise social networks (ESN) generates vast amounts of data, giving researchers and managerial decision makers unprecedented opportunities for analysis. However, more transparency about the available data dimensions and how these can be combined is needed to yield accurate insights into the multi-facetted phenomenon of ESN use. In order to address this issue, we present a framework of available data dimensions and describe possible methods and insights as well as opportunities and limitations of each data dimension. We then adopt this framework exemplary to comprehensively analyze an empirical ESN case.

Keywords Enterprise social networks • Social software • Social network analysis • Data dimensions • Mixed methods • Case study

1 New Opportunities

Work culture within and between enterprises is subject to constant changes towards more flexibility, especially in the sense of location- and time-independent work [1, 2]. In the context of changing communication and collaboration practices, systems that support connected and distributed work, such as Enterprise Social Networks (ESN), play an increasingly important role. They facilitate the generation of large quantities of user generated content [3, 4] and simultaneously lead to a high degree of interconnectivity among a companys' employees [5, 6]. Since almost every interaction in the system leaves a persistent digital trace [7], the increasing use of ESN produces a considerable amount of data. This "revolution in the measurement of collective human behavior" [8, p. 66] gives researchers and managerial decision makers unprecedented opportunities to analyze and explain such systems. In this context Chen et al. [9] use the term "Business Intelligence 2.0" to emphasize that

S. Behrendt (✉)
Bundeswehr University, Neubiberg, Germany
e-mail: s.behrendt@unibw.de

A. Richter
University of Zurich, Zurich, Switzerland
e-mail: arichter@ifi.uzh.ch

J.H. Mayer, R. Quick (eds.), *Business Intelligence for New-Generation Managers*,
DOI 10.1007/978-3-319-15696-5_8

the type of data analyzed is user generated and structured differently from other systems for BPM, CRM or ERP.

Yet, there seems to be a lack of transparency about the available options and likely implications of concrete decisions on the sources that should be adopted in an analysis. Therefore, in this chapter we pick up the keyword “Business Intelligence 2.0” and explain which methods can be applied to analyze ESN and which questions can be answered by doing so.

Our chapter in particular informs and supports people who are responsible for the introduction and implementation of an ESN or similar systems for communication and collaboration. We furthermore want to address users who can profit from the added value of an ESN by a constant evaluation of best practices in their daily business. Due to these various requirements different metrics and methods need to be applied jointly.

2 Overview of Types of Data and Analysis Methods

In the following we will present different types of data and associated analysis methods. Data on user interactions on such a platform are for example saved in log files and provide information about the extent of usage (*usage data*). Additionally, the users generated content, e.g. in the form of written text or images, can be analyzed (*user-generated data*). Moreover, connections between users are established as soon as users interact with one another, e.g., by “following” others or answering to previous posts (*structural data)*. With time, users get a picture about the platform itself and make their own experiences (*user perception*). In the following we will describe each dimension in detail, including possible insights, data collection approaches and a short discussion of each data dimension.

2.1 Activities

As soon as someone uses an ESN, a digital trace is left behind. Almost all functions within such a system create *usage data,* which is collected by cookies, log files, page tagging, web beacons, and packet sniffing [10]. Alternatively, direct access to the underlying databases can facilitate its export. This covers quantitative and partly accumulated data, such as:

- accessed web pages and frequency of visits,
- the number of downloads and origin of visitors (locations),
- the time stamp and duration,
- the amount of created/edited content (most often divided into different types of content like status message, comment, blog entry, etc.) and also

- the number of groups created (divided into different types of groups, e.g., open, closed, etc.).

Goal of the Analysis

The analysis of usage data does not only provide an overview of the usage intensity of the ESN, but allows drawing conclusions on what content was accessed by whom, when, how often, and for how long. It sheds light on key activity areas of the platform and helps to identify how many registered users are really active and how many stay rather passive. The differentiation of different types of content and groups enables, among other things, the identification of most preferred content, most active groups and whether conversations are held rather openly or privately. Depending on the functional range of the platform advanced analyses are possible too, for example, the number of questions that were actually answered or the amount of time passed until a response was posted. These data can be evaluated in order to understand the technologies in use, or to improve the design and usability, to accelerate content updates, or even to improve the website's performance. Figure 1 shows exemplarily the temporal development of user statistics and the development of different content types.

Possible Approach

Already for quite some time it is common to log user actions on web pages in various ways (so-called web tracking). Usage data are either stored on the server (in the form of log files) or on the user device (e.g., by JavaScript tags, by so-called count pixels or by cookies) after which they can be analyzed and then visualized by different web-analytics tools. Likewise, this procedure can be applied to ESNs. Detailed data, such as the number of different contents, are often provided by the ESN itself and are most often aggregated and visualized via some kind of dashboard. For further processing (like for example the above image, created with Microsoft Excel) an export to the desired format is necessary. A significant advantage is that this data can be exported at any time and across any timeframe (depending on the platform settings). However, organizational events and constraints need to be considered as well. For example a community managers' promotion of certain topics, or the presentation of important organizational communiqué can influence this data indirectly.

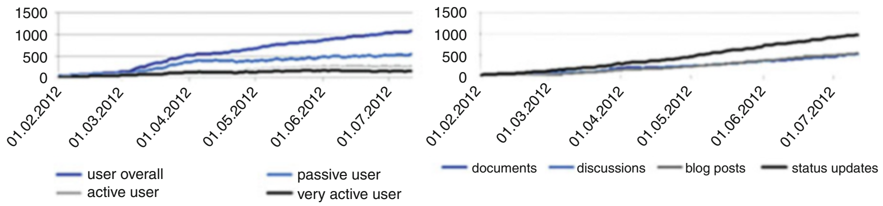

Fig. 1 Possible representation of usage data

Discussion
Usage data are logged automatically and continuously by the different mechanisms. Due to the fact that the tools often provide data in an already pre-processed way, an analysis is possible without much effort (see e.g., Yammer in Sect. 3). Furthermore, data can be processed graphically in order to quickly and easily show changes over time. Nevertheless, analysis possibilities depend both on the web tracking tools used and the ESN itself. If certain actions are not logged, it is almost impossible to retrieve them later on, or at least it requires additional effort to retrieve them, e.g., with the help of own tracking mechanisms. Similarly, the export of this data for further use in other tools (e.g., Excel) may be restricted or require a lot of effort.

2.2 Content

Although usage data provides information on the amount and distribution of activity on a given website, it hardly allows for any conclusions on why users have visited the platform, whether they have achieved their goals, and if the platform was useful in this respect. In order to better understand and interpret these activities, it is helpful to take a closer look at *user-generated data*.

Some examples for these are:

- status messages, blog entries, and comments,
- appointments & tasks or
- wiki pages.

Goal of the Analysis
Insights accessible via an analysis of user-generated content can be of very different type and can be achieved via various methods including content analysis, sentiment analysis, text mining, or genre analysis. Content analysis tries to draw replicable conclusions from textual data to its context [11], it allows automatic discovery of new, previously unknown information [12]. Hence, a content analysis can identify topics that are currently being discussed intensively or extract communication practices of users. This illustrates how and for what purpose the ESN is used. Sentiment analysis aims to determine a person's attitude towards a specific topic [13]. Hence it is possible to discern the employees' mood, so-called sentiments, between the lines of written text. By taking network structures into consideration, it is even possible to make statements about distribution patterns of sentiments within an organization [14]. These distribution processes develop as people are influenced by the emotional state of other participants during electronic communication [14, 15]. Text mining allows for discovering new information in written communication, or finding patterns across datasets [12] by using linguistic, statistical, and machine learning techniques. In a genre analysis, one or more communication genres are manually assigned to each content element corresponding to their purpose. Communication genres are "socially recognized types of communicative

actions [...] which are habitually executed by members of a community and which pursue a defined social goal" [16]. They are therefore well suited to describe communication practices and usage patterns within groups. For example Riemer and Richter [17] conducted a genre analysis of an enterprise social network and found that its usage in the enterprise context differed greatly from that in the private context. Usage was more work-related than some upper managers expected. Unwanted behavior, like non-work-related chatter, does not automatically emerge when social technologies are applied in the enterprise environment.

Summarizing, by analyzing the content, it is possible to verify if the ESN is used the way it was planned at the time of introduction or if new (even better) ways of use have evolved.

Possible Approach

In order to analyze user-generated content effectively, an export of selected content is necessary. This can be realized either via a platform's own export function, by RSS feeds or directly via the underlying data base. After an appropriate processing of the data, which often includes anonymization of users, text mining methods can be used to analyze the data. In the following, genre analysis and sentiment analysis shall be presented as examples.

Sentiment analysis Besides functional content, a user also communicates sensations, feelings or opinions, e.g., about a certain product, a person or an issue. These sensations are called sentiments and can be extracted from unstructured texts [13]. Apart from the actual parameter value (positive/negative), the strength of the respective value can be determined or peculiarities of textual communication like emoticons, abbreviations or sarcasm can be considered [18, 19].

Genre analysis During a genre analysis content is analyzed manually with the aim of identifying certain ways of communication that are regularly used by a group and serve a defined social purpose [16]. Every type of content is attributed one or more genres of communication in the process. Figure 2 shows an exemplary result of a genre analysis where, in this case, the platform serves mainly for the exchange of opinions, but less so for the generation of ideas.

Discussion

Both methods deliver qualitative results and allow a better understanding of user behavior. Since the analysis is based on unstructured data, the results will always be subject to errors or a certain indetermination. This affects both the automated and manual analysis, because human interpretation of a text also allows different opinions and while analyzing large numbers errors can never be completely eliminated. Differences are especially visible in the amount of effort necessary. An automated text analysis may require certain preparatory (structuring) measures, such as PoS tagging, categorization or grouping [12]. Manual analysis, on the other hand, requires reading and a good understanding of the texts. Here, the size of a text can quickly become a restriction and the analysis is subject to a larger time delay. Consequently, a continuous evaluation becomes very difficult and can only be handled by random sampling or respectively over a fixed span of time.

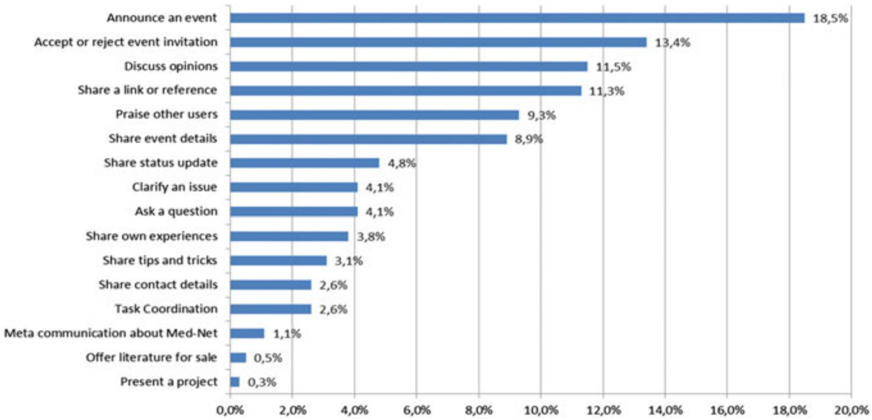

Fig. 2 Distribution of possible genres of communication

2.3 Relations

As soon as users of an ESN interact with one another, relations develop between them, the so-called *structural data*. The study of the connection between different persons, the so-called network analysis (SNA), has been common practice in social sciences for a long time [20]. However, in the social sciences, these relations were often created manually, for example, by means of interviews, which is a painstakingly slow process. While using an ESN, connections of all kinds develop automatically the moment users interact in any way on the platform. Be it by commenting, rating or linking the entry of another user or by following or becoming friends with someone (depending on the platform features). Hence, connections are established between two persons, between a person and content, or even between different contents.

Goal of the Analysis

Basically, a SNA provides insights into the structure of analyzed objects and into how they are related to one another, or whether certain patterns exist. If a network analysis is not only performed at a certain point of time, but over a span of time, this allows to discover developments within the network, so-called network dynamics [21]. If it is also possible to determine the directivity of a relation, statements about action and reaction within a network become possible (e.g., user A follows user B, whereupon user B decides to follow user A).

Based on the fundamental metrics of network analysis like centrality and density [22] statements are possible on:

- how fast information spreads within a network,
- how the actions of different users affect the information exchange,
- or how important or visible certain actors are in the network.

Starting from the original analytic aims in sociology it can be determined how people communicate with one another. In this way, companies can analyze their own communication structures and identify, e.g., bottlenecks or dependencies. According to [23], a different perspective on communication is also possible. The authors differentiate between a "conventional" view of "communication *in* organizations" (i.e. how communication takes place within organizations) and another view, namely that communication *constitutes* an organization. Based on this perspective, statements can be made, e.g., on how communication influences the organizational structure or on how the predefined formal structure of a company (e.g., defined in terms of an organization chart) differs from the so-called informal structure (defined by unplanned relations and interactions between employees). For executives, this offers the possibility to identify and understand the true nature of collaboration in their organization, and hence to better support it [24].

Possible Approach

In order to evaluate these relations a social network analysis (SNA) is well suited. In social sciences a network analysis according to Freeman [25] is characterized by four criteria:

1. the analysis of social relations between actors as an important element of social order,
2. the systematic collection and analysis of empirical data,
3. the graphical representation of this data, and
4. mathematical and computer-aided formal models to obtain abstractions of this data.

Data obtained in this way can be visualized, e.g., as a graph (cf. Fig. 3). A graph in this sense is a set of vertices (often also called nodes) representing the actors in the network paired with a set of edges (often also called ties) that represent relations between actors [26].

To establish connections or a graph it is necessary to clearly formulate the analytical focus. This determines which actors need to be considered and how the relationship developing between them will be defined. Consequently, the required data need to be exported from the ESN and processed. The analysis or visualization is facilitated by different tools like R[1] or Commetrix.[2]

Discussion

A social network analysis shows connections that are not visible using other analysis methods. However, the method can produce various results, which is why it is important to clearly define the analytical focus beforehand. This not only determines the definition of actors and relationships, but also relevant metrics and visualization types.

[1] http://www.r-project.org

[2] http://www.commetrix.de

Fig. 3 Graph representation of a network

2.4 Experiences

With time users make different experiences with the ESN. This has a large influence on how they perceive the system. Hence, they develop their own view or respectively their own opinion about the ESN (*user perception*). Users' experience of and the attitude they develop when using a platform provide insights into their experiential life [27]. Still, they hardly ever communicate it explicitly via messages in the ESN.

Goal of the Analysis

The data treated so far offer an objective (within the limits of what is possible) view on the events in the ESN. Interviews or surveys allow gathering subjective impressions of persons involved and improve the understanding of user practices. Practice has pointed out that companies show particular interest in statements on use and optimization potential (cf. Table 1). Especially the use (for the company) of an ESN comes within reach by this method, as it is rather difficult to quantify the economic value of such a system due to its malleable character [28].

Possible Approach

In order to determine usage practices it is necessary to ask the users directly about them. One way to do this is in the form of interviews or questionnaires. The latter are well suited to collect answers for precise questions in a large scale and can be conducted online, e.g., in the company's own intranet or respectively directly in the ESN. Interviews, on the contrary, are well suited to collect qualitatively better responses and obtain personal opinions or to drill down on certain topics. Both methods require the definition of concrete questions beforehand based on which an

Table 1 Benefits of an ESN

Use	Optimization potential	Usage practices
Employee satisfaction (due to the new type of communication) Time savings (e.g., to find necessary information for problem solutions) Content quality Cost savings (e.g., by lower travel costs)	Satisfaction with the ESN Problems while using the ESN	Aim of using the ESN Identification of concrete use cases and best practices

interview guideline or an online survey is created. The evaluation of interviews is performed manually to a large degree since the given responses need to be interpreted correctly.

Discussion
The collection of such qualitative data offers a good way to triangulate the results obtained so far from other data dimensions. They render the data more tangible by supplying the necessary context, albeit only as a selective survey. Similar to the social network analysis, interviews or questionnaires can provide many different results. They demand good preparation and are very time-consuming (preparation, execution, analysis). This also includes ensuring the compliance with data privacy policies and company agreements, e.g., by integrating the works council at an early stage. Equally, it is necessary to grant employees enough time for participation parallel to their full working day and to handle results transparently at all times. Table 2 gives a summarizing overview about each data dimension.

3 Mix of Methods in Practical Application

All methods treated so far allow different insights and have individual strengths and weaknesses which we want to illustrate with two examples from practice.

For the first example we take a look at the cloud-based enterprise social network “Yammer”, which is currently being used by more than 200,000 companies according to their own declaration and which was taken over by Microsoft in the summer of 2012. For several years Yammer has been offering simple and clear statistics on *usage data* that provide every user with an overview of activities in their network. One of the things to mention is the growth of the network over a certain span of time, measured by new members, and messages. Moreover, Yammer analyzes the number of actually active members that performed an action at least once in that time—be it only changing between two different group feeds. Additionally, there is information about the five most active groups as well as the most popular ways of access (e.g., web client or mobile app) (Fig. 4).

On top of that, Yammer offers the so-called “leader boards” wherein, for a certain span of time, the most active (in terms of messages) or most popular

Table 2 Data dimension overview

Data dimensions	Characteristics	Exemplary data collection methods	Exemplary data analysis methods
Activities (usage data)	Data can originate from various sources The automatic collection results in an extensive amount of data The quantity and quality of an analysis depend on the features of the underlying system, the export options, and the complexity of the database structure	Log files; Tracking pixel; cookies	Web analytics
Content (user generated data)	Is documented in a corresponding context / related communication (threads) Requires manual preparation (e.g., data selection or pre-processing) Can be analyzed manually or automatically Allows for subjective bias in manual analysis Supports multilingual settings	Structured content export	Genre analysis; Sentiment analysis; Text mining; Content analysis
Relations (relational data)	Different types of relations Are affected by platform features and intended tie design Allow for the analysis of network dynamics and evolution	Structured content export	SNA; Dynamic network analysis
Experiences (perceptional data)	Must be documented manually and sporadically Can be assessed on a sample basis only Allow for a deeper understanding of user intensions and the underlying context Require a huge effort to prepare, conduct, and analyze Allow for subjective bias in the collection and analysis process	Interviews; Questionnaires	Content analysis

(in terms of "Likes") users as well as further personal activity indices are shown. This approach on the one hand clearly targets "gamification", but on the other hand also helps identifying influencers within the network.

As explained above, these automated analyses of usage data do not shed light on contents actually exchanged. Therefore, a study published in 2010 qualitatively analyzed more than 1,000 messages over Yammer at Capgemini with the help of a genre analysis [29]. Identified usage patterns show how and for what purpose employees use Yammer, in this case mostly for discussions and problem solutions. Hence, they provide insights into how the ESN supports collaboration at Capgemini

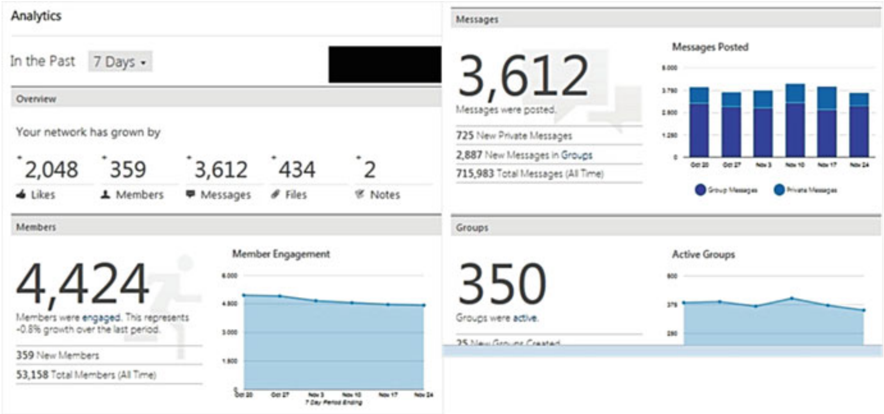

Fig. 4 Automatic processing of usage data in Yammer

and show the role and added value of the platform inside the company. Furthermore, personal interviews with selected users were conducted for the study in order to learn more about the motivation and current challenges using Yammer in the company.

The second example deals with the evaluation of the "San-Netz", an online social network for training medical officers of the German armed forces comprising 1,200 registered members at the moment of evaluation [30]. The applied mix of methods was used to analyze all above mentioned data dimensions, i.e. qualitative and quantitative methods were combined.

For the *analysis of the usage* data 23 months were taken into consideration. Here, it was mainly interesting to see a major part of topic-focused communication take place in groups with restricted access. General knowledge exchange, on the contrary, was in areas open to all members. The frequency analysis of different types of content showed surprisingly many contents of the type "*appointment*" (33 %) which was confirmed by the *genre analysis*. Here, 1,155 messages from 204 users in 5 selected San-Netz groups were analyzed. With a 44 % share *coordination of meetings* was the major part of communication. This clearly shows that a mix of methods can confirm the result of a single method.

The conducted *interview study*[3] came to the conclusion that the hierarchy of the German armed forces (respectively the military structure) barely affects communication. It was even said that the threshold to address a higher rank is lower in San-Netz than it is, e.g., in the barracks. However, the *social network analysis*[4] yielded contradictory results. Here, it became evident that hardly any hierarchy-spanning

[3] 13 Interviews with officers/officer candidates from different ranked were conducted.

[4] Analysis of 445 connections based on 1,155 messages by 204 users

- Nodes: users that generated a content, e.g., appointment, blog, article, comment
- Edges: comments on initial contents

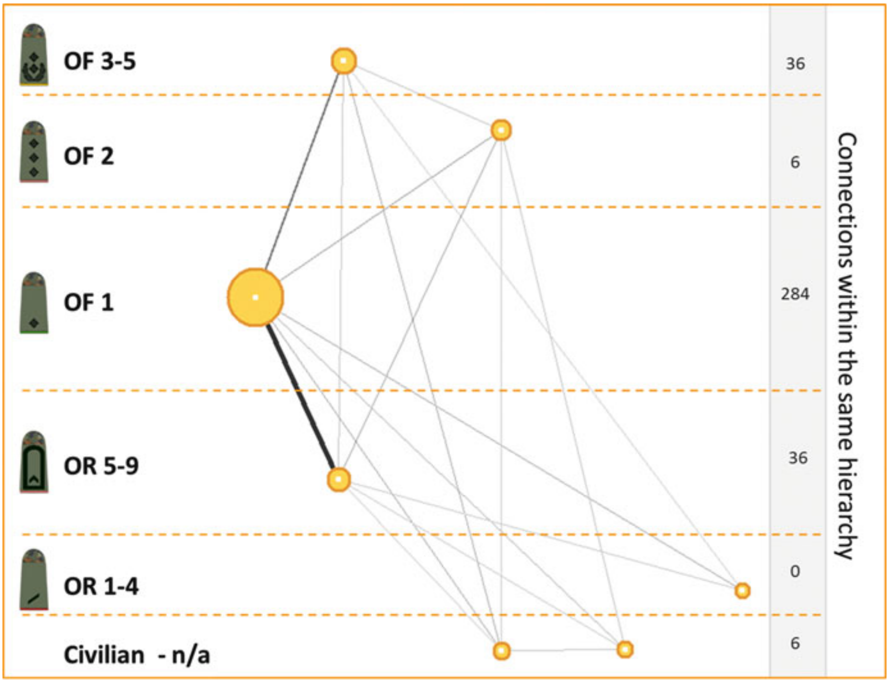

Fig. 5 Illustration of rank-spanning networking

networking takes place. There even emerged so-called bridgeheads in that lieutenants formed a connection between higher and lower ranks, as can be seen in Fig. 5.

Moreover, the SNA showed an uneven distribution of connections as there are only a few people keeping the network together. Although the analysis of usage data already showed that certain people create particularly many contents, only the additional social network analysis revealed the role of these people for the network stability. The usage data also showed that there were certain points of time where more users joined the platform. All of this clearly shows that the results of some methods on their own lack the explanatory power to correctly understand the events inside the ESN. Only by means of data triangulation [31] it becomes possible to increase the explanatory power of the gained insights. In this way, the distribution, conditions, and consequences of patterns of action or network practices can be investigated and a comprehensive picture of social phenomena can be drawn [32]. In the case of the San-Netz the individual analysis results partly confirmed results of other methods. However, they also revealed contradictions in that, for example, the impressions that users get from using the network substantially differ from the measured "reality". This shows that such a mixed methods approach is a suitable means to obtain a more realistic picture of such a network. Summarizing, a mixed method approach can yield four distinct effects [30]: the mutual confirmation of results, the detection of conflicting results, the clarification of observed phenomena and the revelation of new insights.

4 Conclusion

The communication inside a connected organization makes a wide range of different data (Activities, Content, Relations, Experiences) available for analysis. The applicable analytical methods and the questions that these analyses can answer are equally diverse. We argued that a mixed methods analytic approach can produce better results than a single method approach, because it considers combinations of different sources of evidence. A mixed methods approach is not only applicable to the evaluation of an ESN for research, but it also creates additional value for organizational decision makers, as the evaluation results are more significant and more comprehensive. Hence, the analysis of these four data dimensions yields valuable insights for relevant business decisions. Yet, just because it is *possible* to analyze almost anything it is not *necessary* to actually do so. The analysis of an ESN should be preceded by a concrete question or respectively a goal based on which required metrics are identified and an approach is developed. This step bears a certain liability for persons responsible for the platform. Especially the evaluation should help improve the understanding of structures and processes inside the organization; however, it should not support the surveillance of individual employees by means of personal data. In this context, requirements of data security and active company agreements play an important role. It is necessary to develop techniques for anonymization which comply with individual people's rights, but simultaneously answer the company's questions as good as possible. If generally only an analysis in aggregated form is possible (e.g. without a possible identification of single users), the possibilities to analyze cross-links or typical user profiles cease to exist, e.g., "users active in group X are also mostly active in group Z".

While analyzing collected data it is always important to consider the context of use [20] in order to be able and interpret the data correctly. This can either be the context of the use case of interest or the general guidelines for using the ESN. Therefore interviews are a suitable means, as they enable researchers to reveal the required context. A mix of methods in this regard also offers the possibility to investigate how certain communication patterns influence network structures (or vice versa). In particular the combination of content analysis and social network analysis can help substantially improve the understanding of communication and collaboration processes in organizations as they offer the possibility to detect informal employee networks.

Finally, we want to point out that in companies currently not only available data are subject to change, but also *how* they are analyzed. Most notably a trend should be mentioned, towards an increasing prominence of "self-service business intelligence" or "BI as-a-service", that is the possibility to perform analyses individually and flexibly without being dependent on direct support by the IT department, which is offered by the tools and correspondingly requested by the operating departments. Moreover, modern BI tools more and more become collaborative environments and increasingly offer features for simple distributed or, where necessary, time-displaced collaboration. For example, generated reports can easily be commented or discussed or statuses during an analysis can be bookmarked and shared with other people. Hence, the trend is clearly towards a joint data analysis using the possibilities of increasing interconnectivity, which in turn, provides enough space for future research.

References

1. Majumdar A, Krishna S, Bjorn P (2013) Managers' perceptions of social software use in the workplace: identifying the benefits of social software and emerging patterns of its use. In: Proceedings of the 19th Americas conference on information systems (AMCIS), Chicago
2. Kaiser S, Kozica A (2014) Über Grenzverschiebungen in der neuen, vernetzten Arbeitswelt. In: Richter A (ed) Vernetzte organisation. Oldenbourg Wissenschaftsverlag, München, pp 7–15
3. Richter A, Riemer K (2013) Malleable end-user software. Bus Inf Syst Eng 5(3):195–197
4. Richter A, Koch M (2008) Funktionen von social-networking-diensten. In: Bichler M, Hess T, Krcmar H et al. (eds) World wide web internet and web information systems, vol 2008. Gito, pp 1239–1250
5. Riemer K, Richter A (2010) Tweet Inside: microblogging in a corporate context. In: Proceedings 23rd Bled eConference eTrust: implications for the individual, enterprises and society
6. Trier M, Richter A (2014) The deep structure of organizational online networking. An actor-oriented case study. Inf Syst J. doi:10.1111/isj.12047
7. Aral S, Dellarocas C, Godes D (2013) Introduction to the special issue—social media and business transformation: a framework for research. Inf Syst Res 24(1):3–13
8. Kleinberg J (2008) The convergence of social and technological networks. Commun ACM 51 (11):66–72
9. Chen H, Chiang RHL, Storey VC (2012) Business intelligence and analytics: from big data to big impact. MIS Q 36(4):1165–1188
10. Kumar L, Singh H, Kaur R (2012) Web analytics and metrics: a survey. In: Proceedings of the international conference on advances in computing, communications and informatics. ACM, New York, pp 966–971
11. Krippendorff K (2013) Content analysis. An introduction to its methodology, 3rd edn. Sage, London
12. Ben-Dov M, Feldman R (2005) Text mining and information extraction. In: Maimon O, Rokach L (eds) Data mining and knowledge discovery handbook. Springer, New York, pp 801–831
13. Pang B, Lee L, Aggarwal CC et al (2008) Opinion Mining and Sentiment Analysis. Found Trends Inf Retr 2(2):1–135
14. Hillmann R, Trier M (2012) Dissemination patterns and associated network effects of sentiments in social networks. In: 2012 IEEE/ACM international conference on advances in social networks analysis and mining
15. Christakis NA, Fowler JH (2009) Connected. The surprising power of our social networks and how they shape our lives, 1st edn. Little, Brown and Co, New York

16. Yates J, Orlikowski WJ, Okamura K (1999) Explicit and implicit structuring of genres in electronic communication: reinforcement and change of social interaction. Organ Sci 10(1):83–103
17. Riemer K, Richter A (2010) Social software: agents for change or platforms for social reproduction? A case study on enterprise microblogging. In: Proceedings of the 21th Australasian conference on information systems, Brisbane
18. Thelwall M, Buckley K, Paltoglou G et al (2010) Sentiment strength detection in short informal text. J Am Soc Inf Sci 61(12):2544–2558
19. Davidov D, Tsur O, Rappoport A (2010) Semi-supervised recognition of sarcastic sentences in Twitter and Amazon. In: Proceedings of the fourteenth conference on computational natural language learning, pp 107–116
20. Schnegg M (2010) Die Wurzeln der Netzwerkforschung. In: Stegbauer C, Häußling R (eds) Handbuch Netzwerkforschung. VS Verlag für Sozialwissenschaften, Wiesbaden
21. Trier M (2010) Struktur und Dynamik in der Netzwerkanalyse. In: Stegbauer C, Häußling R (eds) Handbuch Netzwerkforschung. VS Verlag für Sozialwissenschaften, Wiesbaden, pp 205–217
22. Jansen D (1999) Einführung in die Netzwerkanalyse. VS Verlag für Sozialwissenschaften, Wiesbaden
23. Blaschke S, Schoeneborn D, Seidl D (2012) Organizations as networks of communication episodes: turning the network perspective inside out. Organ Stud 33(7):879–906
24. Allen J, James AD, Gamlen P (2007) Formal versus informal knowledge networks in R&D: a case study using social network analysis. R&D Manag 37(3):179–196
25. Freeman LC (2004) The development of social network analysis: a study in the sociology of science. Empirical Press, Vancouver
26. Brandes U (2010) Graphentheorie. In: Stegbauer C, Häußling R (eds) Handbuch Netzwerkforschung. VS Verlag für Sozialwissenschaften, Wiesbaden
27. Schultze U, Avital M (2011) Designing interviews to generate rich data for information systems research. Inf Organ 21(1):1–16
28. Richter A, Heidemann J, Klier M et al (2013) Success measurement of enterprise social networks. Tagungsband Wirtschaftsinformatik, In
29. Riemer K, Richter A, Bohringer M (2010) Enterprise microblogging. Wirtschaftsinformatik 52(6):387–390
30. Behrendt S, Richter A, Trier M (2014) Mixed methods analysis of enterprise social networks. Comput Netw. doi:10.1016/j.comnet.2014.08.025
31. Denzin NK (1970) The research act in sociology: a theoretical introduction to sociological methods, Methodological perspectives. Butterworth, London
32. Hollstein B (2010) Qualitative methoden und mixed-method-designs. In: Stegbauer C, Häußling R (eds) Handbuch Netzwerkforschung. VS Verlag für Sozialwissenschaften, Wiesbaden, pp 459–470