Chapter 24
Extending Social Network Analysis with Discourse Analysis: Combining Relational with Interpretive Data

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Abstract Online occupational communities are a rapidly growing phenomenon and will become increasingly important to firms in the future. This growth has been mirrored by scientific innovations: major advances have been made with regard to technology, software development and statistical modeling. However, we are often left with only partial information: although we might be able to gather very detailed and massive relational data from for example online communities, we often overlook information on the ties that bind. While we are provided with an increasingly detailed topology of a network this does not allude to what content is at stake. We therefore propose to combine Social Network Analysis (SNA) and Discourse Analysis (DA) in order to reach a deeper understanding of the community. Data from an ongoing study of an online occupational community were analyzed as an example using SNA and DA. We present findings from SNA and are able to complement this relational information with interpretive findings from DA. We contribute to the methodological literature on online communities, in particular in the fields of SNA and DA.

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24.1 Introduction

In response to the mushrooming developments around the Internet in general and social media in particular, we recently see major advancements in tools and technology that facilitate data collection for social network analysis (SNA) and mining. One might even argue that approaches toward social network research are technology-driven. The ability to be able to 'data-crunch' seduces many researchers to do exactly that. However, sometimes this abundance in information leads to false hopes: although enormous data-sets can be studied in a certain way, this does not automatically improve our knowledge about the phenomenon under study. For example, when investigating networks it is of course necessary to investigate the network topology. For this, advanced technology in the field of data mining is of the essence and it needs to be combined with SNA tools. Nevertheless, whenever the researcher is interested in the actual content of the network as well, these advanced methods often fall short of expectations. We have a lot of information on the nodes and the structure connecting them, but we fail to spot the content of ties. In this article, we propose that it is sometimes useful to complement advanced approaches toward the collection and analysis of social network data with an interpretive approach, for which we chose discourse analysis (DA). By doing so, we are able to offer additional explanations to what we see when performing SNA. Furthermore, we might be able to interpret already existing explanations about the network structure more accurately. We argue that it can often be beneficial to not only rely on a single method, when the combination of methods potentially yields valuable insights.

Recently, scholars called for more use of mixed methods in social research [1]. Often, the execution of only statistical analyses is perceived as not sufficiently covering the field of research, or leading to neglect of relevant information from the empirical data. On the other hand, qualitative studies are often experienced as too detailed, too diverse, and findings are thought of not to be generalizable [2]. In this study, we combine two methods. Specifically, Social Network Analysis in combination with Discourse Analysis is used, thereby responding to calls for research in this direction, in particular in the field of information systems [3]. Data stem from a case study of an online occupational community. Publicly available message board postings are used as indicators of network ties for Social Network Analysis (SNA), and the content of the postings as data for Discourse Analysis (DA).

Network research focuses on relations and patterns of relations rather than on (single) actors and their attributes [4, 5]. It can incorporate data from different sources (e.g., qualitative, quantitative, graphical data, [5]). The structure of a network is important, as is the embeddedness of actors within the network. Calculations of various network parameters, such as density, centrality and brokerage shed light on the position, activity and influence of actors in the network. Within discourse research, the focus is on language use. A discourse is defined as 'a particular way of talking about and understanding the world (or an aspect of the world)' [6:1]. Language is seen as a web of meaning and sensemaking. Within discourse analysis this web is traced, and the meaning that actors ascribe to words is investigated.

This article is structured as follows. First, we provide a short review of research into online communities. Next, in the approach section we describe in detail how we applied the two approaches in the present study, and why they complement each other. We illustrate how the two approaches can fruitfully be combined in methods and analyses. We conclude with a discussion, where we point out future research directions.

24.2 Research into Online Occupational Communities

A growing number of communities mainly interacts online [7], due to the rise of the global Internet and improved technology [8–10]. Within online communities, computer-mediated communication plays a prominent role: language is the main channel of expression and social interaction. Computer-mediated discourse is 'the communication produced when human beings interact with one another by transmitting messages via networked computers' [11:612]. Online communities differ from actual communities due to their restriction of social interaction to online communication. Despite this restriction, complex social interaction takes place in online communities [12]. Communication as the main way of social interaction in online communities can therefore provide unique rich data: discourse manifests itself in written and spoken text, and can be accessed through the analysis of message board postings, as several studies have shown [13, 14].

Studies of online communities typically employ a variety of data analytical methods but pay scant attention to the variegated manner in which content of the communication can be analyzed. A new research stream uses community data as input for analysis and increasingly includes content analysis [15], but also here various mathematical models, survey research and statistical methods prevail. For example, Bagozzi and Dholakia [16] conducted research into an open source software community, employing a survey and analyzing it using structural equation modeling. Franke and Shah [17] also use a survey in order to investigate how community users share among and assist each other. Similarly, a community around Apache software has been studied by Franke and von Hippel [18] by means of a survey. Often, motivations to contribute to community knowledge are investigated, such as in the case of the Linux kernel community [19], a community about library software [20], a community about computer-controlled music instruments [21], firm-hosted communities in general [22] or different virtual communities [23]. Other research was interested in behavior of community members [24], or sharing among members [25]. There are some studies that employ qualitative methods. Case studies [26–31] and ethnographies [7, 32, 33] are dominant in that domain. However, studies that combine approaches are scarce. For example, Fauchart and von Hippel [34] combine a grounded theory approach with a survey; but the findings from the grounded theory part serve as input for the survey, and are not actually combined in the analysis. Similarly, O'Mahony and Ferraro [35] develop a theoretical model using an ethnographic approach, and later develop a survey that highlights one part of the theoretical model. They also limit their analysis to these two different parts.

The above review by far does not mention all research that has been conducted in the field of online communities; nevertheless, these studies represent the methodological approaches that are typically used, and the problems that are addressed. However, many studies could profit from a more in-depth analysis of the ongoing conversation in communities, especially since many of the mentioned studies into online communities are positioned within or touch upon the field of computer-mediated communication. This type of communication lends itself to be studied from a social network perspective, as well from a more content-oriented or discourse perspective: all necessary information is often at hand, as we will see in our illustrative analysis. Thus, we believe that an integration of social network analysis and discourse analysis is a fruitful approach to study computer-mediated communication in online occupational communities. In the next section, we illustrate how this depth could be reached. We do so by first computing degree centrality of community members and explain what this measure expresses. Next, we will continue by analyzing the same data in a different way, using discourse analysis. We will then show that the combination of methods leads to a much deeper understanding of the problem under study.

24.3 Providing Networks with Meaning

Network research is interested in the topology of a network – the structure – and the position of individuals in this structure. There are two main streams of research: one focuses on the structural side of networks, and accordingly presumes that individuals are influenced by this structure. On the other hand, the position of the individual can be studied: depending on the number of social ties, the kind of ties, length of paths and such measures, an individual can access the network and surrounding individuals, and is therefore able to tap into her social capital [36]. To illustrate the point we want to make in this study, we conduct a straightforward analysis of our data and compute degree centrality of community members, based on message board postings. In social network analysis simple indicators such as degree centrality are frequently employed. Centrality is a critical concept which has led to an increasingly finely tuned set of centrality measures to cater for specific theoretical aims [37,38]. In this case study the degree centrality suffices; our goal is not to make claims about prominence, status or brokerage in this online occupational community, but rather to show that any social network measure – in this case degree centrality – can potentially profit from the combination with an interpretive method – in this case discourse analysis.

Discourse analysis provides a strong analytical tool for the study of text since it 'focuses on how social relations, identity, knowledge and power are constructed through written and spoken texts in communities (. . .)' [39]. Within discourse analysis, important words are traced in conversations. In addition, use of words that are central to the dominant discourse can be traced back to individual actors. The focus lies on the analysis of the structuration of meaning within a network. Here, structure is formed by language, in the form of written text. Adopting elements of Laclau and Mouffe's discourse theory [40], language is believed to be socially constructed: 'Language use is a social phenomenon: it is through conventions, negotiations and conflicts in social contexts that structures of meaning are fixed and challenged' [6:25]. Discourse is structured around nodal points: a sign, or word, around which other signs are organized. The signs around this nodal point derive meaning from their relation to it, but the nodal point also transfers meaning upon the surrounding signs.

24.4 Setting and Methods

The case study that is described in this article has been conducted among the community of Dutch cake decorators. The community operates independent of a firm or organization, membership is voluntary and free of charge. The website was launched by a number of Dutch cake enthusiasts in 2004. At the time of writing, the website has about 10,000 registered members (with daily newcomers) and about 500 regularly active members (members who post several times a month, and posted in the past more than 150 messages). Members differ in age, gender, education and background, and left a total of more than 1.3 million postings. Postings are linked to topics; any registered member can open a topic or post about an existing topic. The top ten users are responsible for more than 12 % of the total number of postings. The average number of messages posted daily is more than 600. Data for this article were collected from a single day on one sub-forum of the website. Following Fairclough [41], data were selected according to the identification of *cruces,* which are defined as moments of crisis. This conceptualization is slightly modified as moments of crisis are called events. Not only moments of crisis trigger what Fairclough had in mind: 'such moments of crisis make visible aspects of practices which might normally be naturalized, and therefore difficult to notice; but they also show change in process, the actual ways in which people deal with the problematization of practices' [41]. It is argued that other, non-crisis events may also visualize social practices, simply through above average frequency of social interactions. Events in this manner are therefore defined as the days with most forum postings. We selected one such day and extracted our data from the online community web site.

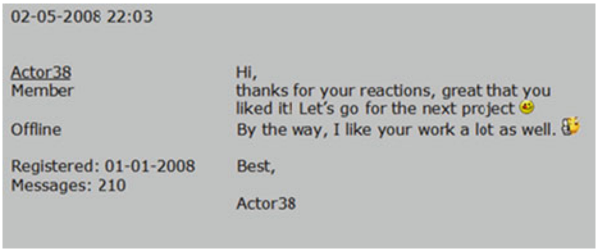

Fig. 24.1 Example of a typical message

Table 24.1 Two-mode matrix of message board postings

	1	2	3	4	5	6
38	1	0	0	0	0	0
39	0	1	0	0	0	0
40	1	0	1	0	0	0
41	0	0	0	0	1	1
42	0	0	0	0	1	0
43	0	0	0	0	0	1

24.4.1 Social Network Analysis

For the SNA part of our analysis, 636 postings were analyzed, posted by 106 different members. A posting contains several pieces of information: text, time stamp, and source. Figure 24.1 shows an example of a typical message.

As a first step of the social network analysis, data was entered into a 2-mode matrix. This means that we entered actors in rows, and events in columns. An event was defined as a topic on the forum. A network tie was defined as the simultaneous presence of postings at the same topic. Table 24.1 shows an example of such a matrix.

In the rows, we can find the actors (actors 38, 39, 40, 41, 42 and 43). The columns represent events, defined as topics: shown are topics 1, 2, 3, 4, 5 and 6. We see that actor 38 and 40 both are present at topic 1, which from our perspective means that they have a tie. The same goes for actor 41 and 42 and topic 5, and actor 42 and 43 at topic 6. The 2-mode matrix was then projected to a 1-mode, so that the matrix presented only actors. Projection followed Bonacich [42] and was executed in Ucinet [43].[1] The projected network from the example in Table 24.1 then looks like this (Table 24.2):

[1] 'Given a binary incidence matrix A where the rows represent actors and the columns events, then the matrix AA' gives the number of events in which actors simultaneously attended. Hence AA' (i,j) is the number of events attended by both actor i and actor j. The matrix A'A gives the number of events simultaneously attended by a pair of actors. Hence A'A(i,j) is the number of actors who attended both event i and event j' [43].

Table 24.2 Projected 1-mode matrix of message board postings

	38	39	40	41	42	43
38	0	0	1	0	0	0
39	0	0	0	0	0	0
40	1	0	0	0	0	0
41	0	0	0	0	1	1
42	0	0	0	1	0	0
43	0	0	0	1	0	0

Table 24.3 Normalized degree centrality

Actor	Normalized degree centrality
25	17.534
61	17.421
33	15.894
38	14.593
40	14.310

This step led to a valued network which was dichotomized at the level of co-presence in postings, using Ucinet [43]. That is, all values above '1' were transformed into '1'.

Having prepared the data for the most important part of our analysis, we computed degree centrality [38] in Ucinet [43]. Analysis is based upon the following: 'The number of vertices adjacent to a given vertex in a symmetric graph is the degree of that vertex. For non-symmetric data the in-degree of a vertex u is the number of ties received by u and the out-degree is the number of ties initiated by u.' [43]. The underlying formula is expressed as

$$\Sigma(\mathrm{cmax} - \mathrm{c(vi)})$$

divided by the maximum value, where c(vi) is the degree centrality of vertex vi, given vertices v1... vn and maximum degree centrality cmax.

We then normalized the data, in order to show their relative values. The normalized degree centrality is the degree divided by the maximum possible degree expressed as a percentage [43]. We present the results from this calculation in Table 24.3. Actors 25, 61, 33, 38 and 40 appear to be most central in this network.

In this section, we explained in detail what kind of data we used to calculate a normalized degree centrality measure. In the next section, we will describe how we implemented the next step of our analysis: discourse analysis.

24.4.2 Discourse Analysis

At this point, we have gathered information on the network topology: we know that the network features a core-periphery structure. Furthermore, we identified the most

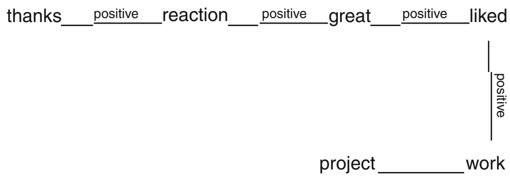

Fig. 24.2 Example of mini-discourse analysis

central actors, at least in terms of normalized degree centrality. The next step will be to supplement this network with meaning: what is it that circulates in this network, in terms of content and meaning? In order to fill in the picture, a combination of discourse theory [40] and critical discourse analysis [41] was adopted. Discourse analysis is an interpretive approach, and is considered a qualitative method [44]. Therefore, analysis relies on the interpretation of the researcher, instead of formulas. Discourse analysis differs significantly from other approaches that use text as data, such as content analysis [45, 46] or NLP techniques. These approaches tend to categorize text, assign numbers to categories or portions of text, and then calculate statistics. However, discourse analysis is concerned with the actual *meaning* of a message, rather than values assigned to it. That is, when looking at the message as shown in Fig. 24.1, the number of words is irrelevant. The important aspect is the meaning of the message: Actor38 is grateful, expresses confidence in the next project, and reciprocates compliments. Discourse analysis thus delivers categories of meaning rather than numbers, and tries to explain how actors attach meaning to their messages.

A discourse is defined as ‘a particular way of talking about and understanding the world (or an aspect of the world)’ [6:1]. Within discourse theory, words form a web of meaning that can be traced through the analysis of language. Discourses are arranged around *nodal points,* or *floating signifiers.* Floating signifiers are ‘signs that different discourses struggle to invest with meaning in their own particular way’ [6:28]. This entails that different meanings are attached to some words in the dominant discourse, or that their meaning is not yet fixed. The meaning of a word is thought to be fixed by *key signifiers.* Key signifiers are words that in themselves are less significant, but become important through the combination with other signifiers. This discursive struggle takes place within frames of reference within which meaning is attached to words, through the combination of key signifiers. For example, the message of Actor38 (Fig. 24.1) only is filled with meaning when combined with surrounding messages. The word ‘reactions’ is meaningless, until we know that ‘reactions’ refers to messages of other actors, who complimented Actor38 on her cake. Thus, the word ‘reactions’ carries a positive meaning (because the reactions were compliments), and is also associated with ‘cake’ (because the reactions were about a cake). However, the analysis of a message only takes into account the words that were actually used in that message. A mini-discourse analysis of this example could look like the example in Fig. 24.2.

Table 24.4 Use of discursive elements of actor 38

	We-them	Compliments and empathy	Competition	Advice and criticism
Actor38	17 %	47 %	15 %	21 %

However, more than one message is needed to conduct a useful analysis in order to be able to say anything meaningful about the actual discourse. We thus carried out a discourse analysis of the messages that we earlier used for the social network analysis. Based upon detailed analyses as shown in Fig. 24.2, we sorted and categorized data. We arrived at the following overarching categories: *we-them, compliments and empathy, competition,* and *advice and criticism*. (Table 24.5 offers some examples of messages that represent the categories.) Discourse analysis provided us with something we lacked: information about the content of the network. We now can put together a picture of how the dominant community discourse might look like: it comprises four different categories.

After having conducted network as well as discourse analysis, we now know how the structure of the network looks like in terms of degree centrality, and also what the prevailing elements of the dominant discourse are. The dominant discourse, in this article, is reflected in the four categories that we found in our messages. In other words, the discourse that is dominant in the community of cake bakers, consists of messages that mainly are concerned with the categories *we-them, compliments and empathy, competition,* and *advice and criticism*. As a last step in this illustration, we want to bring together the two. We argue that it is not only significant to find out what constitutes the dominant discourse, but also how central actors use this discourse. Therefore, we investigated one of the central actors closer. We coded all of the messages that Actor38 left on the message board that day into one of the four categories. Table 24.4 shows the results of this analysis.

In this section, we discussed in detail which methods we used in which way. In the following section, we will report the results of this analysis.

24.5 Findings

After having analyzed our data, we now report our findings. The network graph, a visualization of the earlier calculated degree centrality (Fig. 24.3), shows that the central actors not only feature the highest degree centrality as in number of postings, but are also embedded in the network: they form the very core. This core-periphery structure is typical for online communities, as it also reflects the tendency toward the small world phenomenon [47].

In Table 24.5, we present the four categories that emerged from discourse analysis: they represent the dominant discourse that prevails within the community

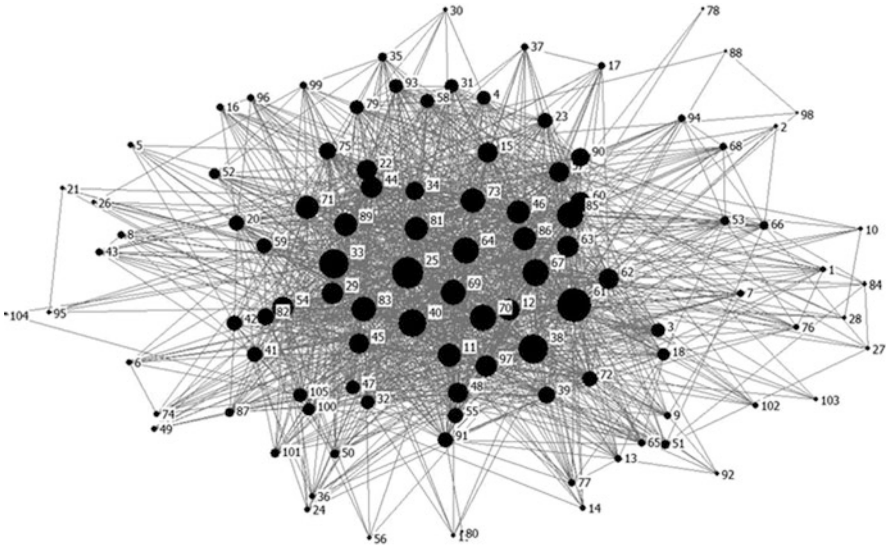

Fig. 24.3 Degree centrality

Table 24.5 Four categories that represent community discourse

Category	Explication and illustration
We-them	Use of abbreviations/jargon; use of real names instead of avatars; references to personal, offline contact; references to we vs. them (we, henhouse, professionals, cake ladies, cake enthusiasts, hunks, dames vs. you, the rest of the forum, the not-Xers, pupils); attributes of we vs. them (make you jealous, have insider stories, won't unveil the mystery, won't post everything on the forum, have capital, can buy stuff vs. we get the picture, are curious, as if I were there, want to come, am sorry, don't know so many people, we are nice too, save money, get a job);
Compliments and empathy	Demonstrations of empathy and emotions (what a relief, next time better, big hug, I know how much it means to you, you can do it, what a misery, you learn from your mistakes, you need to get over it, come on, I saw how sad you were, great, wow, luckily, happy for you); wishes of success and congratulations;
Competition	Use of competitive vocabulary (won a competition, 1st place, you're on 1, top 5, nr. 1, winner, great haul, fun of scoring, passed, challenge, want to have that, jealous); curiosity about other peoples results;
Advice and criticism	Advice as positive support that is sought among community members (great, beautiful, leave it that way, go ahead, perfect, sweet, professional, stylish, smart, will succeed); objective advice in form of questions (is it compulsory?, maybe at home?) criticism dampened by use of smilies or apologies (don't do it, sorry; if I were you ;)

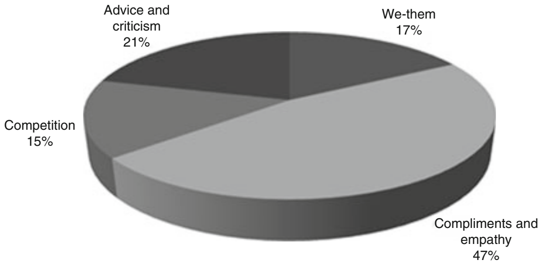

Fig. 24.4 Distribution of messages of actor 38 across four categories

of cake bakers. We add quotes and typical expressions to illustrate the categories. The first category, *we-them*, is about the way community members refer to each other in day-to-day communication. It is very clear that they differentiate between at least two different groups. Second, *compliments and empathy* play an important role in the community discourse. Third, *competition* is related to the former category: although members readily compliment each other, they do also compete for attention, reputation and even more flattering comments. Finally, members engage in *advice and criticism*.

Clearly, a large portion of Actor38's messages belong to the category 'compliments and empathy'. The remainder of her messages is almost evenly distributed across the other three categories. Figure 24.4 visualizes this distribution.

At the end of this analytic illustration, we are able to make claims about the network topology in terms of degree centrality, the content of the network in terms of the dominant discourse, and the use of this discourse of Actor38. Obviously, this last step could be repeated for any actor. In Fig. 24.5, the combination of findings of our illustrative analysis is presented.

Using social network analysis in combination with discourse analysis, we provided our network with meaning. We not only mapped out the topology of the network, but were also able to describe the dominant discourse of the network, and analyzed discourse usage of one individual actor.

24.6 Discussion

The combination of results from social network analysis and discourse analysis yields insights into the topology as well as the content of an online community. Social network analysis provides data about the network and the relations among its actors, whereas discourse analysis allocates meaning within the network. By combining these two methods, we aim to bridge a gap that often separates scientific approaches that might profit from each other. We showed that social network analysis is useful to map out the topology of an online community. This topology is valuable to for example identify central actors in a network. On the other hand,

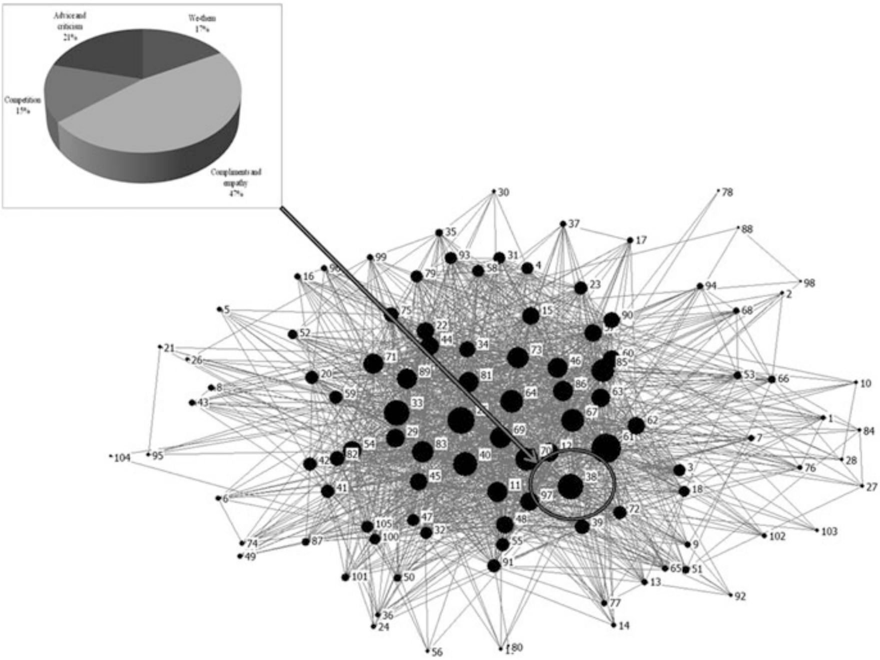

Fig. 24.5 Combination of findings of illustrative analysis

discourse analysis provides the network with meaning: when we know what the community is all about, we can interpret the findings from network analysis more thoroughly. The combination of social network analysis and discourse analysis integrates knowledge about actors' position in a given network with their use of the dominant community discourse. Thus, position can be linked to content, and vice versa.

One of the disadvantages of discourse analysis is that some form of text is needed in order to extract meaning from it. In addition, it takes time to analyze data properly. Furthermore, discourse analysis produces 'soft' data instead of numbers that can be statistically computed, urging some scholars to comment on its low generalizability [2]. However, we have shown that it is possible to conduct discourse analysis and nevertheless transform it into output that is for some more feasible than words. Visualization or statistically expressed numbers sometimes help to make interpretive results more accessible, and therefore enhance the quality of the research. In accordance with the illustration presented in this article, discourse analysis is possibly most valuable when complemented with other methods, as is reflected by researchers calling for more use of mixed methods [1]. Accordingly, future research should be interested in other combinations of discourse analysis with other approaches. For example, different measures of social network analysis might complement findings from discourse analysis [3]. Moreover, when combining the interpretive qualities of discourse analysis with more descriptive content analysis techniques [46], insights might be gained regarding the semantic network within the community.

Future research should take into account the advantages that a combination of methods yields. There are several directions that are as yet unexplored, but promise fruitful results. One possibility is to repeat the analysis we performed in this article several times. This way, results could be interpreted over time and thus reveal network evolution, both in a structural as well as discursive way. Second, it might be interesting to compare the discursive profile of several actors. For example, do profiles of central actors differ significantly from the ones of peripheral actors? Do central actors feature similar profiles? Does a profile predict network position in the future? These are all compelling questions, and answers could help us understand online communities much better than we do now.

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