Mixed methods with social network analysis for networked learning: Lessons learned from three case studies

Anders I. Mørch[1], Renate Andersen[2], Rogers Kaliisa[1], and Kristina Litherland[1]

[1]Dept. of Education, University of Oslo, Norway, andersm@uio.no, rogerska@uio.no, kristitl@uio.no

[2]Dept. of Primary and Secondary Teacher Education, Oslo Metropolitan University, Norway, renatea@oslomet.no

Abstract

In our research we study small group interaction and meaning making in the context of a larger community of people and artifacts. Our research methodology combines social network analysis and content analysis in different ways. The primary purpose of this paper is to explore approaches and demonstrate the feasibility of mixed methods research combining network-level and content-level methods. We report our experiences from three case studies (Get Satisfaction, Canvas, r/place), which include individual variation (innovative approaches toward integration) and a common approach of "zooming in," or shifting perspective between bird's eye and detailed levels of interaction data during analysis (message content, dialogic structure, or visual artifact vs. patterns of users and their interactions). We show that the two sets of methods in combination can eliminate shortcomings of the separate methods used independently.

Keywords

Mixed methods, social network analysis, interaction analysis, discourse analysis, networked learning

Introduction

Networked learning researchers have suggested the "network" metaphor to conceptualize the different forms of social organization in learning activities to help better understand the phenomenon (Ryberg & Larsen, 2010). Haythornthwaite and De Laat (2010, p. 186) referred to networked learning as "an emerging perspective on learning that aims to understand the network processes and properties – of ties, relations, roles and network formations – by asking how people develop and maintain a 'web' of social relations for their own and others' learning". We also understand networked learning along the lines of the "second approach" provided by Dohn et al. (2018) who said, "What makes learning 'networked' is the connection to and engagement with other people across different social positions inside and outside of a given institution. The network is supportive of a person's learning through the access it provides to other people's ideas and ways of participating in practice" (p. 204). This calls for perspectives from several disciplines, including computer supported collaborative learning (CSCL) and computer supported cooperative work (CSCW), and the combination of research methods. In our research we have focused on integrating social network analysis (SNA) and content analysis in three settings: cooperative work, collaborative learning, and collaborative content creation.

For many years qualitative and quantitative research methods have been clearly distinguished as separate and distinct, as they are derived from respectively discrete research traditions with unique underlying assumptions of epistemology. As such, the two approaches differ in their perspective of learning and knowledge. While the primary goal of qualitative research is to clarify the characteristics or attributes of a phenomenon in focal areas, quantitative research attempts to in some way measure the same phenomenon using a wider lens (Widerberg, 2001). In recent years the weaknesses of both methods have received increased awareness and attention, and a possible solution for overcoming the weaknesses has been proposed, which involves the combined use of the two methods, also referred to as mixed methods research (Lund, 2012). The increased interest in mixed methods can be explained, according to Hollstein (2014), as the attempt by researchers to merge the strengths of both qualitative and quantitative methods and, in the process, counterbalance the respective weaknesses of both approaches.

In this paper we present three examples of mixed methods research employed to analyze empirical data in the areas of cooperative work, collaborative learning, and collaborative content creation. Each of the three case studies applies SNA as the quantitative method, combined with one of three alternative content analysis methods: interaction analysis (case 1), discourse analysis (case 2), and visual artifact analysis (case 3). The term *content analysis* is used here as a general term to represent the qualitative method category, not as a reference to its established use for describing the research technique for coding and analyzing segments of textual data, which is outside the scope of our work. The main purpose of this paper is to address how mixed methods research, integrating SNA and content analysis, can be useful in examining a networked learning context, such as online communities like discussion forums on social media or learning management systems. We survey related work on the development and use of these methods (background, concepts, and empirical results) before we embark on our own case studies.

Social Network Analysis and Content Analysis

Researchers in SNA use terminology and procedures from the mathematical graph theory to study networks (De Nooy, Mrvar, & Batagelj, 2011). The basic entities are nodes (vertices) and edges (links, ties). Social network analysis pertains to finding (usually by computer) patterns of relationships of nodes and edges using matrix algebra (matrix representation of "1s" and "0s" with computers) (Scott, 2000). The results of a social network analysis after matrix computation are visual (e.g., sociogram) or structural properties or measurements (e.g., table) of nodes and whole networks (Borgatti, Everett, & Freeman, 2002). For example, the degree centrality measure of a node is the number of ties held by that node, which consists of indegree and outdegree values for a directed graph and degree values for an undirected graph (Freeman, 1979). In plain terminology, degree centrality is an indicator of a person's importance in a community based on the number of interactions (e.g., number of telephone calls or posts and comments in a Facebook group) the individual has been involved in, where high outdegree indicates influence and high indegree indicates popularity (Andersen & Mørch, 2016).

Social network analysis originated in the early to mid-20th century but increased in popularity with the emergence of computers for use in automating the collection and analysis of large networks (tedious or impossible with manual methods) and performing analyses of online social networks (Java, Song, Finin, & Tseng, 2007). At first, primarily sociologists, anthropologists, and psychologists used SNA, but today it also used by political scientists, computer scientists, and information scientists, among others. In many online communities, access to data is simplified by crawling or web scraping, which means that the edges between nodes are openly accessible online and can be captured more easily using SNA tools (Mislove, Marcon, Gummadi, Druschel, & Bhattacharjee, 2007). Sites that allow for this data extraction feature provide an opportunity to measure and study online social networks on a large scale. Examples are public Facebook groups and Twitter lists, which can be accessed with social network analysis tools, such as NodeXL (Smith et al., 2009), among others.

A dual focus is inherent in some social networks, such as those involving persons and affiliations (Breiger, 1974) and those involving persons and mediating artifacts (Harrer, Malzahn, Zeini, & Hoppe, 2007; Suthers & Rosen, 2011), which gives rise to two types of social networks, single-mode (or ordinary) and two-mode (affiliation). A single mode network is represented by nodes and edges as described previously and exemplified by face-to-face (direct) interaction, telephone calls, and online chatting, whereas two networks are required for a two-mode network. A classic example of a two-mode network was examined in an anthropological study where data were collected on 18 women who interacted at one or more of 14 social events in a community in the southern United States (Davies, 1941). By analyzing the patterns of which women were present (or absent) at which events, it was possible to infer an underlying pattern of social ties, factions, and groupings among the women (Breiger, 1974). The discussion forum constitutes the "social event" in online communities and is often represented as a two-mode network, involving two networks of actors and topics, where the latter mediate the former (Harrer et al., 2007; Suthers & Rose, 2011; Andersen, 2018). Social network analysis measurements of two-mode networks are time consuming and are usually transformed into a single-mode network before computation (De Nooy, Mrvar, & Batagelj, 2011). An underlying assumption for inferring relationships in a discussion forum is that when people are sending posts and reply-to comments on the same topic, they are connected by an edge in the equivalent ordinary (single-mode) network (Andersen, 2018; De Nooy, Mrvar, & Batagelj, 2011; Harrer et al., 2007). Suthers & Rosen (2011) suggested using "associograms," which are intermediate representations obtained from lower level write and read events to provide stronger evidence for interaction in discussion forums. There is no intrinsic reason for stopping at two-mode networks; indeed, multimodal networks have been proposed for complex communities (Breiger, 1991) and different types of media (Suthers & Rosen, 2011). In one of our case studies (case 3), a visual network of tiles on a pictorial canvas serves as a third-network that complements a two-mode network of users and discussion threads.

Social network analysis and other network analysis methods give us the big picture of a large dataset of actors, interactions, affiliations, and mediating artifacts. However, the big picture (e.g., a sociogram or a table of structural properties) cannot tell us anything about the detail (content) of the interactions, for example, if two actors who communicate agree about a point of view, if they exchange information to persuade each other, and how they gradually develop understanding over time, which are key aspects of coordination, meaning-making, and collaborative knowledge construction. The social interactions occurring in networked learning environments are supported through dialogue between actors. To understand the dialogue, we need to analyze the content of interactions, for example, through interaction analysis (Jordan & Henderson, 1995), which focuses on how to produce accounts of people's verbal activities in terms of turn-taking and meaning-making (constructing meaning over time). However, it is difficult to evaluate the quality of collaborative learning without tracing the interactive contributions of the individuals involved (Gašević et al., 2019). Therefore, we also explored another example, discourse analysis, which analyses transcripts of discussions and large amounts of text generated during online interactions to gain insight into the nature and quality of students' digital artifacts. In our case, it meant looking for patterns of activity that correspond to meaningful learning and knowledge construction (De Liddo et al., 2011). We make use of interaction analysis in case 1, discourse analysis in case 2, and analyze the visual contributions of the collaborators in case 3.

Previous Work Combining SNA and Content Analysis

In this section we review selected studies that combine SNA and CA, since this is our focus. The selected studies were found by online database searches and chosen due to their relevance to our mixed methods research in networked learning. We were inspired by this work and built on their ideas to create new knowledge.

Martínez, Dimitriadis, Gómez-Sánchez, Rubia-Avi, Jorrín-Abellán, and Marcos (2006) applied a mixed methods approach in three case studies to examine the participatory aspects of learning in CSCL contexts. Social network analysis data was triangulated with data sources that included observations and interviews. Technology was an asynchronous communication tool supporting messages and document sharing (BSCW). Technology supported indirect communication, which pointed toward a two-mode network modeling, i.e., distinguishing two types of nodes (users and shared artifacts, i.e., folders in the BSCW collaboration software in this case). Our work is related in that we use two-mode networks in two of our cases, but we use interaction analysis and visual artifact analysis as our content analysis methods.

De Laat, Lally, Lipponen, and Simons (2007) used SNA with a mixed-methods approach, combining SNA with content analysis and context analysis (online postings and interview data), referred to as a multi-method research framework for studying networked learning. This method is used for understanding message exchanges in online courses. The authors used SNA to zoom in on regions of high density to carry out content analysis, using the outcome of one method to further understand the subsequent method. They also used timeline analysis to capture development over time (beginning, middle, and ending phases). However, they do not refer to artifacts outside the social interactions, as we do in our cases.

Fugelli, Lahn & Mørch (2013) used SNA in combination with interaction analysis to understand the evolution of intersubjectivity in an open source software development community and created an early version of a process model for mixed methods research. This consisted of three steps: 1) identify regions in the network that are interesting from the point of view of intersubjectivity, 2) identify meaning-making processes in the selected regions, and 3) identify the mechanisms that trigger the meaning-making process. Our work was inspired by this research; we developed it further for educational settings and using new theoretical frameworks.

Kolleck (2013) studied social innovations applying a mixed methods approach, combining quantitative SNA and questionnaires with qualitative semi-structured interviews and egocentric network maps. The participants constructed the egocentric network maps during the interviews, the maps providing important data in their own right, but also working as tools to guide the interviewer in asking relevant questions about the interviewees' relationships. This integration of methods provided insights of both the structural characteristics of the studied networks as well as each individual's own understanding of his or her place within them.

Baker-Doyle (2015) employed a tri-model for mixed methods social network analysis to study teachers' support-seeking behavior and experiences. The analysis led to the identification of network members who were unreported by participants in socio-metric survey data yet were nonetheless significant members of teachers' professional support networks. Such a result would have been invisible in traditional SNA analysis. By exploring the characteristics of the relationships, critical moments, and the contexts in which these relationships became engaged, the tri-modal model helped to uncover the invisible networks.

In a recent study on classroom group discussion, Bruun et al. (2018) combined discourse and network analysis methodology to identify relationships between content and group dynamics. The discourse analysis method identified relationships between content and group dynamics, and the network analysis method used the same data to identify meaning-related dynamic structures found in the data. This methodology led to the attainment of greater analytic insights than would have been possible by either of the two methods individually. The strength of the work is an example of connecting discussions and structural representation of the dynamics of the discussion, serving as two reciprocal mechanisms for developing ideas over time in discussion forums.

Three Case Studies

Below we present data from three case studies to provide empirical evidence for our research efforts at exploring alternative approaches to mixed methods research combining network-level and content-level methods. For each case, the context of the study, integration of the methods, and analysis of the empirical data are described. This includes discussion on the integration of the two datasets for each case and what information they provide in total.

Case 1: Get Satisfaction

Context of the study: Get Satisfaction (GS) is a customer engagement platform consisting of a bundle of online communities for involving customers in product development activities, which are the focus of the case study. GS has more than 63,000 online communities and boasts 9,600,000 visitors a month. The online community is structured around questions and answers, organized under four different topic threads: 1) ask a question, 2) share an idea, 3) report a problem, and 4) give praise. The research focus for the case study was identifying the interactions between end users, champions, and professional developers in the online community as they jointly created a shared artifact (a web application) in different processes defined as mutual development (Andersen & Mørch, 2016). The data were collected from the publicly available platform over a six-month period.

Integration of the methods: We integrated two sets of methods in two ways: 1) SNA was used to analyze the whole dataset, which was followed by zooming into a specific region to further investigate in detail from a interaction-level perspective; and 2) SNA data was brought into the interaction analysis by presenting the SNA centrality measures "tagged" or connected to each utterance given by the participants.

Analyzing the empirical data: The data extract presented in Figure 1 was derived from one of the largest discussion threads in the GS online community. The extract shows the beginning of the thread that deals with the topic of "sticky threads" as part of the discussion forum. *Sticky thread* is a term assigned to threads deemed important, appearing before the others in Internet forums. Two end users, three champions, and one developer are part of the extract. Figure 1 illustrates how SNA and interaction analysis are combined during analysis of the empirical data and during visualization of the empirical data (Andersen & Mørch, 2016).

Turn	Actor	Text from discussion thread	nDeg	nBet
1	E_125	Offer sticky or featured topics	3.084	0,00
2	D_5	Hi, End user 125, You can make a reply "sticky" but we don't currently have a mechanism for making a post sticky. If you're a company rep you can use the "Company Update" topic type to post that topic on your company home page, which might partially solve the issue for you. Can you describe your need a bit more?	8.157	8.009
3	E_125	I am a company rep in GS and we got this question from our users a couple of times. They see a post (be it a question or an idea shared), and they suggest making the thread/post sticky. And I just wanted to see if there is a way in GS to do so. Thanks for your reply. I will look into your suggestion.	3.084	0.00
4	C_1	Just got a similar request from one of our users. http://getsatisfaction.com/izea/topic...	1.713	1.484
5	C_7	I've shared this with the product team - I'm working on pulling together a community-manager focused release to help get some of these ideas and bugs all bundled together for maximum awesomeness. Stay tuned.;)	5.042	2.188
6	E_131	Any progress on sticky topics?	3.084	0,00
7	C_7	We're getting closer, but it's a tough change! I'll update over here once we've rolled it out	5.042	2.188
8	C_2	I do think there is room for a "sticky" if we just arrange things a little and have them on the left side bar or the right side bar maybe in a smaller text. FAQ would be ideal. I did a very quick and rough example here but you get my drift lol	6.828	9.112

Figure 1: Excerpt from a discussion thread in GetSatisfaction using format for interaction analysis that extends the Jordan & Henderson (1995) format with two columns: nDeg and nBet, importance according to Degree (ability to find and give information) and Betweenness (ability to block or spread information).

This data extract helps to illustrate the processes that emerge when different stakeholders collaborate and interact when co-creating a shared artifact. In the extract we can see that it is the end-user who initiates the idea for further development of the web application when suggesting the new "sticky feature." What is interesting in this extract is the role of the champions. Champion 2 makes an important decision at the end of the extract. However, we do not know in the outset whether or not to trust Champion 2 regarding the power and quality of the posting. Viewing the postings of Champion 2 from a purely interactive ("here and now") perspective would not reveal the history of his or her previous interactions in the community. When we look at the data taking the

SNA perspective into account, we see that Champion 2 is the most powerful champion in the network, having a degree centrality of 6.828 and betweenness centrality of 9.112. This excerpt is part of a central mass collaboration process defined as bridge building in Andersen and Mørch (2016).

Case 2: Canvas

Context of the study: Canvas is a learning management system (LMS) that simplifies the organization of course content for students, teachers, and administrators in educational institutions. In this study, Canvas was used as a platform for online discussions within a blended bachelor's course (i.e., involving face-to-face and online activities) at a public university in Norway. The main objective of the course was to introduce selected learning technologies and applications and to familiarize students with the central theoretical perspectives of technology-enhanced learning. The course included eight compulsory online discussions on eight different topics, and face-to-face lectures over eight weeks between January and April 2019. The discussions were conducted asynchronously and were text-only. For each week, teachers initiated a new discussion thread based on the topic of the next face-to-face lecture. Each student was expected to make two contributions and respond to at least one other student every week. The primary research focus of the case study was on exploring the potential of social learning analytics (i.e., social network and discourse analysis combined) to support teaching and learning decisions in online learning environments.

Integration of the methods: For the first approach (SNA), the network data of 34 students and 4 teachers were analyzed using NodeXL, a third-party social network tool (Smith et al., 2009). For the second approach (discourse analysis), we used social network analysis metrics (i.e., degree and betweenness centrality) to "zoom in" on the more active and less active students to inform further discourse analysis (Kaliisa, Mørch & Kluge, 2019). Discourse analysis of students' discussion content was performed using Coh-Metrix, a computational linguistics tool for analyzing higher-level features of language and discourse (McNamara et al., 2014).

Analyzing the empirical data: The findings of the first analysis (SNA) revealed information about the characteristics of students' interaction patterns across the eght weeks, with some students demonstrating more activity in the discussion forum than others. However, the findings from the second analytic action (discourse analysis), which examined the actual discussion content, provided greater understanding of the nature and quality of students' contributions that would not have been visible by employing a single approach. For instance, as illustrated in Table 1, the results revealed that the students who had high centrality measures were associated with contributions having higher referential cohesion and syntax simplicity, which means that their text had simple familiar syntactic structures and ideas within the text were well connected. On the other hand, students who had a less central position were characterized with a more narrative style discourse, which implies an informal style of discourse (Kaliisa et al., 2019).

Table 1: SNA centrality and discourse metrics for more active and less active students in Canvas

	More Active Students					**Less Active Students**				
SNA Metrics	S3	S17	S9	S14	S28	S10	S25	S27	S31	S32
Degree	7	6	4	2	3	1	1	1	1	1
Betweenness	94	33	25	0.6	0.0	0.0	0.0	0.0	0.0	0.0
Discourse Analysis Results										
Narrativity	36	78	2.2	71	35	44	70	58	61	93
Deep Cohesion	81	60	0.8	50	80	39	87	93	83	99
Referential Cohesion	51	41	67	46	77	2.7	29	16	20	56
Syntax Simplicity	60	30	15	37	34	23	18	4	11	18

Case 3: r/place

Context of the study: r/place is the name of an event that took place on the social media site Reddit on the first three days of April 2017. During the event, participants had access to a virtual "canvas" (not to be confused with case 2) of 1000 x 1000 single color tiles. The canvas started out empty (all tiles were white), but participants could color (i.e., “place”) tiles on the canvas using any of the 16 colors provided. However, after coloring a single tile (in a single color), each participant had to wait five minutes before coloring another tile. These constraints meant it was difficult to create meaningful objects alone. Within the first day of the activity, the participants began working together to develop and maintain objects. They also developed Reddit communities (discussion forums) to coordinate the construction and maintenance of the visual objects. At the end of the event, over 1 million users had placed over 16.5 million tiles (Reddit, 2017). The data we present here are based on a specific region on the canvas (coordinates x in the 375–529 range and y in the 375–529 range, which became an adaptation of the Mona Lisa) and its related online community, The Mona Lisa Clan.

Integration of the methods: We integrated quantitative and qualitative methods in three ways: 1) SNA helped to “zoom in” on particular regions of interest in the discussions using network degree centrality, as in the first two cases, 2) SNA helped to understand the structural context of the discussions by tagging individual utterances with node degree centrality, as in the first case, and 3) whole discussions are connected to visual objects by a URL tag (e.g., r/monalisaclan are printed in tiles in the Mona Lisa picture, see Figure 2) (Litherland, 2018).

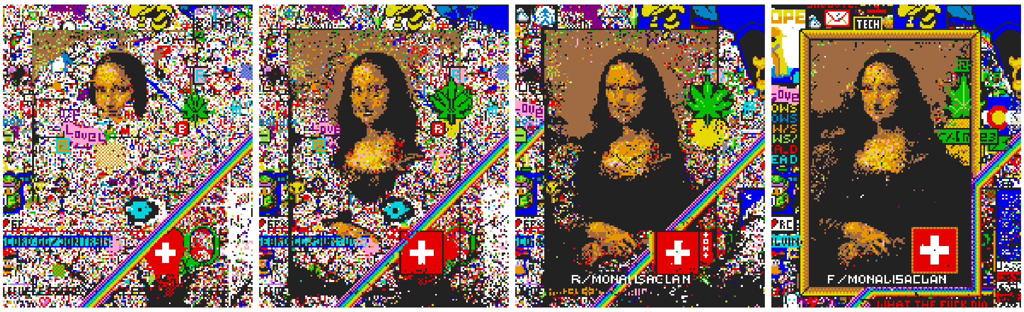

Figure 2: The Mona Lisa visual artifact evolving on r/place

Analyzing the empirical data: The users were not instructed to create URL tags, but many of the 1,500 objects that emerged during the experiment ended up having tags to discussion forums to coordinate construction and protect the region from vandalism from neighboring groups. The application of structural analysis to both visual artifacts and talk (discussion forum posts) to understand the r/place event were undertaken because they were organized as networks of lower level building blocks and analyzed by network analysis methods (relationship of tiles to color and region where they belonged, and relationship of users and who they communicated with). The latter relationship was examined using SNA and the former using visual object placement graph (Figure 3).

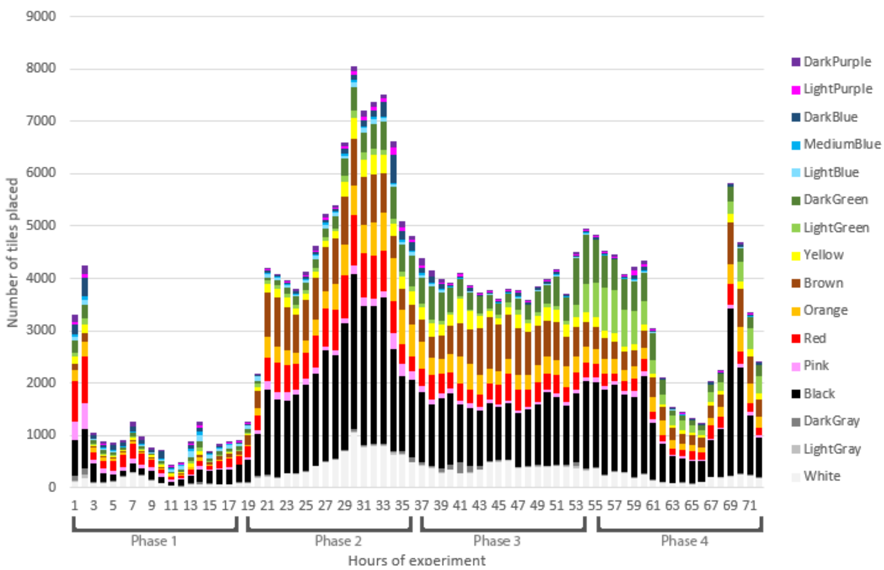

Figure 3: Visual object placement graph: Number of tiles placed by color per hour in the Mona Lisa region on the pictorial canvas.

The two types of networks had similar structures but did not change in the same way. The average degree centrality in the social network was stable at about three for the entire period, i.e., on average three postings per person (sending and receiving messages) in the Mona Lisa Clan discussion forum. The activity on the Mona

Lisa picture revealed a wavier pattern (Figure 3), a dynamic relationship driven by the emergent sub-parts appearing in the image (Figure 2). Thus, we found evolutionary development in r/place in both visual artifacts (pictures were created and maintained over time) and coordination talk (discussion and persuasion). They were not formally connected at the network level but tightly connected at level of meaning making (interaction).

Summary of the Three Cases

Table 2 provides an overview of the different data methods, duration of study, number of participants and networks, and tools used for analysis in the three case studies.

Table 2: Case studies overview of methodological features and choices

Individual case	Qual Method	Quant Method	Collected data and length of study	Networks and nodes (*N*)	Analysis tools used
Case 1: Get Satisfaction	Interaction analysis of the text from discussion forum posts and replies	Social network analysis of the interactions between end users, professional developers, and champions	Postings in the discussion threads in the online community from March 2012 to August 2012	Two-mode network: $N1$ = 229 participants (End users, professional developers, and champions) and $N2$ = 41 discussion threads	UCInet and DNA
Case 2: Canvas	Discourse analysis of discussion forum posts and replies	Social network analysis of students' online interactions	Postings in discussion threads (399) from Jan 2019 to April 2019	One mode network: N = 38 participants (34 students and 4 teachers)	NodeXL and Coh-Metrix
Case 3: r/place	Interaction analysis of the text from discussion forum and visual artifact analysis	Social network analysis of user interactions and analysis of visual artifacts (visual object placement graph)	Discussion threads made Apr. 1st-3rd collected Feb 2018 to Apr. 2019. Visual object placement graph from public data file Apr. 2019	Two-mode network: $N1$ = 161 users, and $N2$ = 72 discussion threads, and a visual object network with $N3$ = 243,103 tiles	Excel and Pajek

The values in Table 2 were partly chosen by the researchers of this study and partly determined by the type of discussion forum analyzed. In cases 1 and 3, the GS and Reddit discussion forums are topic-based, which means participants interacted indirectly, mediated by topic, which required a two-mode network. In case 2, using Canvas, discussants interacted by responding to a posting or comment created by another participant (e.g., like a Facebook group discussion), and interaction was direct, which allowed us to model interaction by a single-mode network. In case 3, a third network was added to the analysis, visual objects network of pixels. This network level representation of a visual artifact was compatible, though not formally connected, with the discussion forum at the network level (both had nodes and edges), thus allowing for structural comparison.

General Discussion

In this section we discuss and compare the various approaches to mixed methods presented in this paper. The focus of our discussion is not on the empirical data in the case studies but on the methods applied and the strengths and weaknesses experienced. Additionally, we compare our approaches with related work.

Lessons Learned

Case 1 (Get Satisfaction) strengths: Employing a mixed methods approach on a large set of data in a mass collaboration context that focuses on mutual development of a shared artifact (web application) was found to be very useful. It provided a rich dataset and two very different perspectives on mass collaboration in an online community. The network level (SNA) yielded an overview of the empirical data serving as a zoom; the interaction level (IA) provided detailed explanations of select segments of the empirical data. This informed a more comprehensive understanding of the phenomenon of mutual development than either method by itself could have done (Andersen & Mørch, 2016). At the interaction level, SNA was used to tag the different participant utterances with network-level data, thus connecting socio-historical structural properties (spanning months to years) with content-specific interaction data unfolding in real time (spanning minutes to days).

Case 1 (Get Satisfaction) weaknesses: Combining two different research methods stemming from very different research traditions and capturing different time spans is not without obstacles. For example the SNA measures may not always be accurate as participants can receive high scores also for rudimentary content and short texts. In addition, the process of coding the empirical data was very time consuming. A better solution could be to scrape and generate SNA data ready for UCInet (Borgatti et al., 2002) directly from a webpage.

Case 2 (Canvas) strengths: The implication derived from the analysis for this case study is that even though social networks on a learning management system do not necessarily show evidence of knowledge construction among students, this process can partly be monitored through discourse analysis, thus empowering teachers to create criteria for teaching and learning decisions. In other words, combining social networks and discourse analyses can provide quick and useful insights for teachers' understanding of their students' cognitive and social characteristics of their learning processes. Consequently, this can be used to empower teachers in creating informed decisions for the purpose of redesigning courses delivered on an LMS to improve networked learning processes (Kaliisa et al., 2019).

Case 2 (Canvas) weaknesses: The main limitation of the methodology presented in this case lies in the complexity of establishing students' learning processes based on the SNA and discourse metrics in combination. Further research is needed to understand how SNA and discourse analysis can be combined to monitor collaborative knowledge construction processes and whether different social ties yield different discourse structures (i.e., through, for example, networks) over time.

Case 3 (r/place) strengths: As we only used data from open Reddit communities, and the r/place dataset itself was openly available, data collection was simple. While the implication for learning might not be obvious, our approach revealed that participants practiced a wide variety of skills pertaining to collaborative content creation, and that actions on the canvas influence the related social networks and vice versa, thus complementing each other. We argue that by viewing r/place through a single lens (e.g., SNA by itself), we would not have been able to reveal this interconnectedness, nor the intra-connectedness within single communities and visual objects.

Case 3 (r/place) weaknesses: Although the mixed methods approach allowed us to capture some aspects of the r/place event, additional work is needed to determine how to further integrate different methods to understand not only the structural aspects of collaboratively created visual objects and their connected communities, but also their qualitative aspects, and how these two realms are complementary in terms of, e.g., meaning-making.

Implications for Learning in Networked Communication

The experimental studies and system building efforts reported by Martínez and colleagues (2006) and Harrer and colleagues (2007) represent early efforts to use SNA in CSCL contexts. Those authors revealed a compatibility of mediating artifacts, such as information sharing systems and collaboration software, and two-mode networks in SNA. Our work was inspired, in part, by their work, but our empirical settings are broader in scope, as we accessed data from commonly available information sharing systems (e.g., public websites and institutional LMS), thus demonstrating the approach to different settings of networked learning like distance education and mass collaboration. Learning can be divided into collaborative learning and individual learning. According to Stahl, Koschmann & Suthers (2006), "CSCL locates learning in meaning negotiation carried out in the social world rather than in the individuals' heads." In the cases reported from here we have studied collaborative learning at the small group level within the context of a larger network of communication. We have studied group interaction and meaning making by content analysis methods mediated by artifacts and more knowledgeable persons. In case 1 & 3 we analyzed argumentation, negotiation, and persuasion about improving a shared artifact, a web application (case 1) or a visual artifact (case 3). In case 2 we analyzed collaborative knowledge construction in a Canvas discussion forum by undergraduate students responding to and advancing understanding of topical questions raised weekly by instructors in a technology-enhanced learning course. All three case studies are conducted in a context of online learning and focus is on networked communication in different ways. In case study 1 and 3, the context is an online discussion forum that mediates the participants' communication. In case study 2 the context is also in an online platform, however the focus is not on analyzing the online communication between students, but on how they use Canvas. Finally, in case 3, the focus of the communication is to coordinate the evolution of a visual artifact (a reconstruction of Mona Lisa in pixels).

The three case studies have in common the mixed methods approach (combining content analysis and SNA). However, we found it is time consuming to carry out the analyses and there are epistemological challenges connected with the methods' originating in different research traditions. Foregrounding research questions with an argumentation for the relevance of combining methods for addressing them can help to counterbalance the weakness. The strength of the mixed methods strategies we employed is that the methods complement each other by providing two distinct views of the data, qualitative and quantitative, which provides a richer understanding of the complexity of large scale (in number of participants) networked learning. From a qualitative perspective we gain insight into the meaning making and collaborative knowledge creation of small group networked communication, whereas from a quantitative perspective, we get a bird's eye view of the important structural properties of the entire network. Taken together these two data sets provide more complete information about networked learning processes.

Conclusions and Suggestions for Further Work

The primary aim of this paper was to explore approaches to mixed methods research combining network-level and content-level methods. We addressed this by presenting three case studies, each applying a different mixed methods research design. Based on the implications derived from the three cases, we argue that mixed methods approaches can offer tools for researchers to capture students' meaning-making and online collaborative learning patterns in a more comprehensible way that would be obscured when using only one of these methods.

This article contributes to the literature by highlighting the potential of an analytic strategy that combines SNA with content analysis. This strategy means having two different levels of information (quantitative and qualitative) providing a macro and micro perspective on the dataset. From a quantitative perspective SNA provides a birds eye view of the total amount of data focusing on mathematical measurements of the actions and interactions in the network, and from a qualitative perspective a content analysis provides an empirical and in depth perspective on selected elements of the data accomplished in part by human interpretation. In total, one can say that the SNA is used as a zoom (macro perspective) for selecting what data to go into depth about (micro perspective). With SNA we identified key actors and their interaction patterns, according to centrality measures. We explored three different methods for content analysis (interaction analysis, discourse analysis, and visual artifact analysis). At the qualitative content level, we zoomed in on specific interactions or content areas, allowing focus on the details of the interactions. Conducting the quantitative analysis involved a four-step method (inspired by Andersen & Mørch, 2016): 1) the data were imported from the online community, 2) a data analysis tool was used to code the statements using thematic analysis, 3) the data were prepared for SNA analysis, and finally 4) a SNA software tool was used for computing centrality measures, Ucinet (Borgatti et al., 2002) in case 1, NodeXL (Smith et al., 2009) & Pajek (De Nooy, Mrvar, & Batagelj, 2011) in cases 2 & 3.

One possible idea for further study is to develop an integrated multi-level interaction analysis methodology, and we suggest two avenues to follow: 1) choose interaction as the unit of analysis and bring SNA level information (structural properties) to this level as parameters (tags) for interaction analysis, as we demonstrated in cases 1 and 3, and 2) start with the social structure as the unit for analysis and bring interaction level information (e.g., discourse data extracts) to this level. We plan to explore this avenue with case 2, using epistemic network analysis (ENA) tools to model learning processes by constructing networks that represent learners' cognitive connections (Shaffer, Collier, & Ruis, 2016). We argue that this might provide us with a thicker and richer description of the data and understanding of the learning processes, as it yields quantifiable and qualitative information about the network and visualization of learning trajectories over time for individuals and groups.

References

Andersen, R. (2018). Mutual Development in Online Collaborative Processes: Three Case Studies of Artifact Co-creation at Different Levels of Participation (PhD thesis). Faculty of Educational Sciences, University of Oslo, Norway

Andersen, R., & Mørch, A. I. (2016). Mutual development in mass collaboration: Identifying interaction patterns in customer-initiated software product development. Computers in Human Behavior, 65, 77-91.

Baker-Doyle, K. J. (2015). Stories in networks and networks in stories: A tri-modal model for mixed-methods social network research on teachers. International J. of Research & Method in Education, 38(1), 72–82.

Borgatti, S. P., Everett, M. G., & Freeman, L. C. (2002). Ucinet 6 for Windows. Harvard, MA: Analytic Technologies.

Breiger, R.L. (1974). The duality of persons and groups. Social Forces, 53(2), 181-190.

Breiger, E.L. (1991). Explorations in structural analysis: Dual and multiple networks of social interaction. New York, NY: Garland.

Bruun, J., Lindahl, M., & Linder, C. (2019). Network analysis and qualitative discourse analysis of a classroom group discussion. International Journal of Research & Method in Education, 42(3), 317–339.

Davis, A., Gardner, B. B., & Gardner, M. R. (1941). Deep South: A social anthropological study of caste and class. Chicago, IL: University of Chicago Press.
De Laat, M., Lally, V., Lipponen, L., & Simons, R.-J. (2007). Online teaching in networked learning communities: A multi-method approach to studying the role of the teacher. Instructional Science, 35(3), 257–286.
De Liddo, A., Shum, S. B., Quinto, I., Bachler, M., & Cannavacciuolo, L. (2011). Discourse-centric learning analytics. Proc. of the 1st Int. Conf. on Learning Analytics and Knowledge. (pp. 23-33). New York: ACM.
De Nooy, W., Mrvar, A., & Batagelj, V. (2011). Exploratory social network analysis with Pajek: Structural analysis in the social sciences (Rev. and exp. 2nd ed., Vol. 34). New York: Cambridge University Press.
Dohn, N. B., Sime, J.-A., Cranmer, S., Ryberg, T., & De Laat, M. (2018). Reflections and Challenges in Networked Learning. In N. B. Dohn, S. Cranmer, J.-A. Sime, T. Ryberg, & M. De Laat (Eds.), Networked Learning: Reflections and Challenges. (pp. 187-212). Cham, Switzerland: Springer.
Freeman, L. C. (1979). Centrality in networks: Conceptual clarification. Social Networks 1(3), 215–239.
Fugelli, P., Lahn, L.C., & Mørch, A.I. (2013). Shared prolepsis and intersubjectivity in open source development: Expansive grounding in distributed work. In Proc. of the 2013 conf. on Computer supported cooperative work (CSCW ’13). (pp. 129-144). New York, NY: Association for Computing Machinery.
Gašević, D., Joksimović, S., Eagan, B.R., & Shaffer, D.W. (2019). SENS: Network analytics to combine social and cognitive perspectives of collaborative learning. Computers in Human Behavior, 92, 562–577.
Harrer, A., Malzahn, N., Zeini, S., & Hoppe, H. U. (2007). Combining social network analysis with semantic relations to support the evolution of a scientific community. In C. A. Chinn, G. Erkens, & S. Puntambekar (Eds.), Proceedings CSCL’07. (pp. 270–279). USA: International Society of the Learning Sciences.
Haythornthwaite, C., & De Laat, M. (2010, May). Social networks and learning networks: Using social network perspectives to understand social learning. Proceedings of the 7th International Conference on Networked Learning. (pp. 183-190). Aalborg DK: Aalborg University.
Hollstein, B. (2014). Mixed methods social networks research: An introduction. In S. Dominguez, & B. Hollstein (Eds.), Mixed Methods Social Networks Research: Design and Applications. (pp. 3–35). New York, NY: Cambridge University Press.
Kaliisa, R., Mørch, A. I., & Kluge, A. (2019, September). Exploring Social Learning Analytics to Support Teaching and Learning Decisions in Online Learning Environments. In European Conference on Technology Enhanced Learning. (pp. 187-198). Cham, Switzerland: Springer.
Kolleck, N. (2013). Social network analysis in innovation research: Using a mixed methods approach to analyze social innovations. European Journal of Futures Research, 1(25), 1-9.
Java, A., Song, X., Finin, T., & Tseng, B. (2007). Why we twitter: Understanding microblogging usage and communities. Proceedings WebKDD/SNA-KDD ‘07 conference. (pp. 56–65). New York, NY:ACM.
Litherland, K. T. (2018). Together You can Create Something More: Social Structures and Practice of 21st Century Skills in Mass Collaboration (Master's thesis). Faculty of Educational Sciences, University of Oslo.
Lund, T. (2012). Combining qualitative and quantitative approaches: Some arguments for mixed methods research. Scandinavian Journal of Educational Research, 56(2), 155-165.
Martínez-Monés, A., Dimitriadis, Y., Gómez-Sanchez, E., Rubia-Avi, B., Jorrín-Abellan, I., & Marcos, J. A. (2006). Studying participation networks in collaboration using mixed methods. Computer-Supported Collaborative Learning, 1, 383–408.
McNamara, D. S., Graesser, A. C., McCarthy, P. M., & Cai, Z. (2014). Automated evaluation of text and discourse with Coh-Metrix. Cambridge, UK: Cambridge University Press.
Mislove, A., Marcon, M., Gummadi, K.P., Druschel, P. & Bhattacharjee, B. (2007). Measurement and analysis of online social networks. In Proc. of the 7th ACM SIGCOMM conference on Internet measurement (pp. 29-42). New York, NY: ACM.
Reddit. (2017). Place datasets (April fools 2017). https://www.reddit.com/r/redditdata/comments/6640ru/place_datasets_april_fools_2017/ [viewed 09.19.19]
Scott, J. (2000). Social network analysis: A handbook. London, UK: Sage Publications.
Shaffer, D. W., Collier, W., & Ruis, A. (2016). A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. Journal of Learning Analytics, 3(3), 9-45.
Smith, M. A., Shneiderman, B., Milic-Frayling, N., Mendes Rodrigues, E., Barash, V., Dunne, C., ... & Gleave, E. (2009). Analyzing (social media) networks with NodeXL. Proceedings of the Fourth International Conference on Communities and Technologies. (pp. 255–264). New York, NY: ACM.
Stahl, G., Koschmann, T., & Suthers, D. (2006). Computer-supported collaborative learning. In R. K. Sawyer (Ed.), The Cambridge Handbook of the Learning Sciences (pp. 409-425). Cambridge, UK: Cambridge University Press.
Suthers, D. and Rosen, D. (2011). A unified framework for multi-level analysis of distributed learning. In Proc. of the 1st Int. Conf. on Learning Analytics and Knowledge (LAK ’11). (pp. 64-74). New York, NY: ACM.
Widerberg, K. (2001). Historien om et kvalitativt forskningsprosjekt. Oslo: Universitetsforlaget.