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Reviewing mixed methods approaches using Social Network Analysis for learning and education

Dominik Froehlich¹, Martin Rehm², Bart Rienties^{3*}

¹University of Vienna, Vienna, Austria

²Pädagogische Hochschule Weingarten, 88250 Weingarten, Germany

³Open University UK, Jennie Lee Building, Milton Keynes, UK

¹dominik.froehlich@univie.ac.at

²rehmm@ph-weingarten.de

³bart.rienties@open.ac.uk

*Corresponding author

Abstract. Across the globe researchers are using social network analysis (SNA) to better understand the visible and invisible relations between people. While substantial progress has been made in the last 20 years in terms of quantitative modelling and processing techniques of SNA, there is an increased call for SNA researchers to embrace and mix methods developed in qualitative research to understand the what, how, and why questions of social network relations. In this chapter, we will reflect on our experiences with our latest edited book called “Mixed Methods Approaches to Social Network Analysis for Learning and Education”, which contained contributions from 20+ authors. We will first review the empirical literature of Mixed Methods Social Network Analysis (MMSNA) by conducting a systematic literature review. Secondly, by using two case-studies from our own practice we will critically reflect on how we have used MMSNA approaches. Finally, we will discuss the potential limitations of MMSNA approaches, in particular given the complexities of mastering two ontologically different methods.

Keywords: Social Network Analysis, Mixed Method, MMSNA, systematic review

Acronyms

AMOT Amotivated Students:

AD Academic Development

CET Cognitive Evaluation Theory

CSCL Computer Supported Collaborative Learning

EMER External Motivation to External Regulation

EMID External Motivation to Identified Regulation

EMIN External Motivation to Introjected Regulation

IMES Intrinsic Motivation to Experience Stimulation

IMTA Intrinsic Motivation to Accomplish

IMTK Intrinsic Motivation to Know

MMSNA Mixed Methods Social Network Analysis

MM Mixed Methods

MRQAP Multiple Regressions Quadratic Assignment Procedure

PBL Problem Based Learning

SDT Self-Determination Theory

SNA Social Network Analysis

VLE Virtual Learning Environment

10.1 Introduction

Social network theory postulates that individuals' behaviour can be predicted by the underlying network structure of relations in which they are embedded. Social network analysis (SNA) investigates these structures and helps to determine and understand social interactions between individuals (e.g., workers, managers, students, cohorts); and in contrast to main disciplines in the social science research tradition expands the focus to also include larger entities (e.g. groups, communities) (Scott, 2012; Wassermann & Faust, 1994). Over the last two decades, a wealth of mostly quantitative research (i.e., systematic empirical investigation of observable phenomena via statistical, mathematical, or computational techniques using numbers) in social science and education in particular has shown that social networks and ties of individuals to others can have a significant influence on a myriad of different aspects, including attitudes, behaviours, and cognition of individuals, groups, and even wider society (e.g., Borgatti, Mehra, Brass, & Labianca, 2009; Cela, Sicilia, & Sánchez, 2015; Coburn & Russell, 2008; Daly & Finnigan, 2011; Hommes et al., 2014; Moolenaar, 2012; Rienties & Tempelaar, 2018).

SNA researchers typically distinguish between two types of data, namely objective and subjective SNA data (Hanneman & Riddle, 2005; Scott, 2012). Objective data refers to the actual trace data of interactions between individuals nodes, such as email conversations (McCallum, Wang, & Corrada-Emmanuel, 2007), discussion threads (De Laat, Lally, Lipponen, & Simons, 2007; Peña-Ayala, Cárdenas-Robledo, & Sossa, 2017), or Wikipedia feeds (Rehm, Littlejohn, & Rienties, 2018). This type of "objective" data sheds light on who central actors might be within a network, or whether sub-groups might be present within a larger network structure.

Similarly, a large number of SNA researchers have used so-called subjective (or self-reported) SNA data approaches (Coburn & Russell, 2008; Daly & Finnigan, 2011; Rienties, Johan, & Jindal-Snape, 2015), whereby in a closed (i.e., a clearly delineated group of participants: department; village, classroom) or open network approach participants are asked SNA questions like "who are your friends", "who do you go for advice", "from whom have you learned in the last four weeks". For example, in our own research we found that how students form friendship and learning relations significantly influenced how they maintained learning relations over time, which significantly impacted on their academic grades and long-term academic performance (Rienties & Tempelaar, 2018). Similarly, in a medical programme Hommes et al. (2012) found that although motivation and academic integration significantly predicted academic performance of first-year medical students, the largest predictor for performance were the respective ties with whom students were learning from.

As argued by Froehlich, Rehm, and Rienties (2019), "quantitative" SNA data might under- or over-estimate complex and dynamic underlying network structures (De Laat & Lally, 2004; Jindal-Snape & Rienties, 2016; Rienties & Hosein, 2015; Rienties et al., 2015). There may be several methodological and ontological issues with collecting such subjective and objective SNA data (Moolenaar, 2012; Scott, 2012). More specifically, subjective data might be subject to issues of recall (Neal, 2008), remembering social interactions, and the type of information shared.

Several researchers (Cela et al., 2015; Crossley, 2010; Dado & Bodemer, 2017; Froehlich & Brouwer, Forthcoming; Rienties & Hosein, 2015) have urged SNA

researchers to embrace and mix methods developed in qualitative research (i.e., a scientific method of observation to gather non-numerical data) to understand the what, how and why questions of social network relations. For example, if “objective” SNA data identified that a person was central in an email network, this does not automatically imply that this person is also central in the respective company (e.g., an administrator standardly included in conversation). Indeed, our own work using SNA data from a range of specific historical Wikipedia pages indicated were mostly uploaded by a couple of dedicated people (Rehm et al., 2018), but in hindsight these were primarily people who had support roles, rather than the actual historians who just sent the information to the administrators.

In a case study reported by Froehlich, Mamas, and Schneider (2019), a similar phenomenon was observed when studying advice networks: newcomers appeared to be quite central in these networks. This, however, does not mean that they play an actual central role in the respective networks. Instead, it is an artefact produced by the newcomers’ rather unfocused attempts in seeking contact to many people in the early days within a new organizational environment.

Therefore, a number of researchers have started to explore whether integrating SNA approaches with other (quantitative and qualitative) approaches could help to increase our complex understandings of social networks (Cela et al., 2015; Dado & Bodemer, 2017; Froehlich & Bohle Carbonell, 2020; Froehlich, Rehm, et al., 2019), while at the same time providing a potentially more robust, reliable, and interlinked approach. In our forthcoming book, we argued that an increasing number of social network studies make use of mixed methods (MM) to generate their findings (Froehlich, Rehm, et al., 2019). This surge in recent MMSNA research is based upon the realisation that quantitative (or formal) and qualitative SNA each have their very own sets of strengths and weaknesses (Crossley, 2010). For example, qualitative SNA (e.g., asking people in an interview with whom they have worked intensively in the last month, and what their lived experiences were working with these people) often lacks an overview of the structural properties of a network. However, this often is a central piece of relational thinking. For example, it would be rather difficult to ask all employees of a large enterprise a sociocentric question via interviews and build a coherent network structure.

In contrast, as argued by Froehlich and Brouwer (Forthcoming) quantitative SNA often may be “too abstract” to consider what is actually exchanged between dyads (e.g., working on a joined research project, sharing a new idea of a potential patent). Furthermore, quantitative SNA may fail to account for any fluctuations of the dyads’ relationships over time (i.e., “I worked very intensively together with Jennifer two month ago, but now she has moved to a different project, but I am still occasionally going for a beer to discuss how our project is going, and picking her brain on my new project”). Hence, mixed methods social network analysis (MMSNA) can be particularly relevant in unveiling (social) complexities within organisations, and educational research in particular. For example, Froehlich and Gegenfurtner (2019) referred to MMSNA as being useful to measure the transfer of training. Additionally, Froehlich and Bohle Carbonell (2020) proposed MMSNA to investigate issues around team and group learning (Rienties & Tempelaar, 2018).

According to Froehlich, Rehm, et al. (2019) MMSNA may be formally defined as “any SNA study that draws from both qualitative and quantitative data, or uses

qualitative and quantitative methods of analysis, and thoughtfully integrates the different research strands with each other”. Here, we define mixing as the combination of types of data being used. Both qualitative and quantitative data need to be incorporated in a study. Alternatively, we can consider whether the methods being used may be more quantitatively- or qualitatively-oriented (Hesse-Biber, 2010). Finally, we may look at the “mixing” itself: Are different strands of research integrated in a thoughtful, purposeful manner (Schoonenboom, Johnson, & Froehlich, 2018)? While these considerations are helpful, they only provide information on the nature and the potential of mixing methods.

However, the formal definition of MMSNA by Froehlich, Rehm, et al. (2019) may tell us little about the actual form that MMSNA studies may take. For example, when would a study using social network concepts (e.g., cohesion, number of links) be classified as an SNA study, or MMSNA study, or just a qualitative or quantitative study? Does a MMSNA study require both quantitative (e.g., SNA graphs) and qualitative SNA data (e.g., ethnographical mapping of a network in a company), or can a MMSNA study also contain multiple qualitative data, multiple quantitative data, or a combination of the two? Therefore, in this chapter we will first review 44 studies that have used MMSNA in the field of learning and education. Afterwards, we will provide two studies with practical applications from our own practice of how one could potentially mix SNA with other methods (and vice versa).

10.2 Methods

In this chapter, we will first provide a systematic literature review of the MMSNA literature. While there are a range of studies that have systematically reviewed SNA studies (Borgatti & Halgin, 2011; Borgatti et al., 2009; Carpenter, Li, & Jiang, 2012), and in education (Golonka, Bowles, Frank, Richardson, & Freynik, 2014; McConnell, Hodgson, & Dirckinck-Holmfeld, 2012; Van den Bossche & Segers, 2013; Vera & Schupp, 2006), and CSCL and SNA in particular (Cela et al., 2015; Dado & Bodemer, 2017), there is to the best of our knowledge no systematic literature review of MMSNA. Afterwards, using our experiences when writing the MMSNA book (Froehlich, Rehm, et al., 2019) we will critically reflect on two exemplars of MMSNA. We are not claiming that these exemplars are the best in MMSNA, but are mere reflections of how we as authors in SNA and mixed methods research have tried, and often failed, to combine MMSNA. We hope that by sharing our lessons learned it will inspire others to think about adopting similar approaches.

10.2.1 Study 1 Systematic literature review

As a first part of this chapter we conducted a systematic literature review of MMSNA studies that was originally published by Froehlich (2019). Texts were retrieved from the Education Resources Information Center using a pre-defined set of keywords. This set was developed and refined in multiple rounds of test searches and in consultation with MM researchers. Given that this study focuses on methodological approaches ra-

ther than any knowledge generated thereby, the procedures of back-tracking and forward-tracking to find additional MMSNA studies seemed unwarranted. Also, further databases were not queried, given that the focus of this chapter is the presentation of a novel approach to analyzing texts and methods, and not a systematic literature review. Throughout the process, the search strategy was discussed with experts in the fields of literature reviews and MM.

10.2.1.1 Data collection

Texts were retrieved from the Education Resources Information Center using a pre-defined set of keywords. The data set was the repeatedly refined in consultation with MM researchers. As search terms, Froehlich (2019) used two blocks of keywords: 1) The application of social network analysis through the search terms (social network analys* OR SNA or social network* or network analys*). 2) Searching for MM studies only by applying the following search terms: (mixed method* OR MMR OR multiple method*) OR (qualitative OR unstructured interview* OR open interview* OR semi-structured interview* OR focus group* OR grounded theory OR grounded theories OR ethnograph* OR etnograf* OR ethnograf* OR phenomelogic* OR hermeneutic* OR life history* OR life stor* OR participant observation* OR open interview OR thematic analyses OR content analyses OR observational methods OR constant comparative method OR field notes OR field study OR audio recording) AND (quant*). For time period, Froehlich (2019) opted to search for articles and studies between 1996-2018. The two blocks were connected using an “AND” operator. In order to focus on the recent studies,

The search yielded 657 results. The title and abstracts of all found publications were screened before the full texts were read. 159 papers were excluded because they did not fit the field of learning and instruction; 52 papers were excluded because they were not empirical; 346 papers were excluded because they did not use social network analysis; 21 papers were excluded because they did not include MM (i.e., either quantitative or qualitative data or quantitative or qualitative methods of analysis); 35 articles were excluded because they did not meet any of the other inclusion criteria (for example, the full text of five texts could not be retrieved). In the end, 44 texts were selected to be included in the study. For further details of the search strategy, and inclusion and exclusion criteria we refer to Froehlich (2019). Eventually, 44 texts formed the basis for Study 1.

10.2.1.2 Data analysis

First, the methods used in each of the selected articles were coded. Second, we applied SNA to investigate this network of methods. For the selected articles, the 32 methods used were coded for data collection (e.g., semi-structured interviews or sociometric surveys) and analysis (e.g., linear regression analyses or multiple regression quadratic assignment procedures). The temporal order of the methods used (e.g., sequential or parallel designs) was then used to build a relational dataset.

Quantitative SNA (Wassermann & Faust, 1994) was used to analyse the relational dataset created. While this method was originally used to depict relationships between human beings (Freeman, 2003), as also highlighted by Rehm et al. (2018) these procedures can also be applied to uncover the relations between concepts, or, as in our

case, research methods. The 32 identified methods were the nodes used, while the ties represent the sequence of their usage. Note that the network is also weighted, as the ties were aggregated (e.g., if two studies were coded to show a sequence of X to Y, this would result in a weight of “two.”). While 287 relationships were coded, only 98 ties were present in the aggregated, weighted graph. The network data was cleaned and prepared using the igraph package (Csardi & Nepusz, 2006) for R (R Core Team, 2014); Gephi (Bastian, Heymann, & Jacomy, 2009) was used to visualize the network and calculate basic key metrics.

10.2.2 Study 2 Objective SNA with content analysis

In the second part of this Chapter we explore the use of two exemplars of use of MMSNA approaches. In Study 2, we applied an objective SNA with content analysis in a context of an online summercourse in economics in the Netherlands. Study 2 was chosen to illustrate how one quantitative SNA approach could be combined with a more qualitative approach of content analysis. In Study 3 we explored a different MMSNA approach using an open SNA approach with qualitative follow-up analysis.

10.2.2.1 Context and setting

In order to provide a critical perspective how MMSNA could be used in practice, in the second part of the chapter we explored two practical MMSNA studies. In Study 2 we used an exemplar of an online summer course followed by 82 participants at a business school in the Netherlands in 2005/2006 (Rienties, 2010, 2019; Rienties, Tempelaar, Giesbers, Segers, & Gijsselaers, 2014; Rienties, Tempelaar, Van den Bossche, Gijsselaers, & Segers, 2009) to explore how objective SNA could be combined with content analysis of actual discourse. This summer course is part of a wider summer course program that has been offered since 2004 to over a thousand students and has been fully integrated in the admission and application processes of the respective business school (See Rienties, Giesbers, et al., 2012; Rienties et al., 2009; Rienties, Tempelaar, Waterval, Rehm, & Gijsselaers, 2006; Tempelaar et al., 2011). All students who subscribed to the International Business & Economics Bachelor program were informed of the opportunity to participate in this online summer course via a letter and email with information about the course and a link to a prior knowledge test. Based on their score on the prior knowledge test, students could decide to voluntarily enrol. Students with a low prior knowledge score who did not enrol received a follow-up e-mail recommending enrolment.

The primary aim of this course was to bridge the gap in economics prior knowledge with the requirements for the degree program (Giesbers, Rienties, Tempelaar, & Gijsselaers, 2013, 2014; Rienties, Giesbers, et al., 2012; Rienties et al., 2009; Rienties et al., 2006; Tempelaar et al., 2011). This online course was given over a period of six weeks in which learners were assumed to work for 10-15 hours per week. The participants never met face-to-face before or during the course and had to learn economics using the virtual learning environment “on-the-fly”; that is learners had to learn how to use the VLE and PBL learning phases while undertaking the program. In particular, the aim of this research was to determine how students’ motivation might

have been related to their participation in online discussion fora. Moreover, we also investigated whether collaboration within these fora might have led to a higher cognitive discourse among students.

2.2.2.2 Instruments used

First, we collected *objective SNA data* from the discussion forums and calculated both Freeman's degree of Centrality (Wassermann & Faust, 1994), as well as ego network density. Second, we employed *content analysis* in order to analyse what students were contributing to the fora and possibly contributing to our understanding of underlying processes of learning and knowledge construction (Rehm, Gijssels, & Segers, 2015; Rienties, Giesbers, et al., 2012; Rienties et al., 2009). The content analysis was based on an instrument developed by Veerman and Veldhuis-Diermanse (2001), which distinguished between non-task related and task-related discourse activity. Departing from this data, we linked individuals' degree centrality with the cognitive level of their discourse. The content analysis of Veerman and Veldhuis-Diermanse (2001) has been used and validated by other researchers (e.g. Rehm et al., 2015; Rienties, Giesbers, et al., 2012; Rienties et al., 2009; Schellens & Valcke, 2005). When comparing various content analysis schemes, Schellens and Valcke (2005) conclude that the Veerman and Veldhuis-Diermanse (2001) scheme is particularly suited for analysing knowledge construction among novice students. Veerman and Veldhuis-Diermanse (2001) make a distinction between so-called *non-task related* (1 planning; 2 technical; 3 social; 4 non-sense) and *task-related discourse activity* (5 facts; 6 experience/opinion; 7 theoretical ideas; 8 explication; 9 evaluation). Three independent coders coded all messages. The network data was cleaned and prepared using UCINET (Borgatti, Everett, & Freeman, 2002); Netdraw (Borgatti, 2002) was used to visualize the network and calculate basic key metrics.

Finally, in order for us to draw conclusions on the impact of motivation on the discussion fora, we used the *Academic Motivation Scale* by Vallerand et al. (1992), which builds on the well-established Self-Determination Theory (SDT). According to Ryan and Deci (2000, p. 56), intrinsic motivation is "... a critical element in cognitive, social, and physical development because it is through acting on one's inherent interests that one grows in knowledge and skills". In a sub-theory of SDT, Cognitive Evaluation Theory (CET), social and environmental factors play an important role in determining what facilitates and what hinders intrinsic motivation. More specific, in SDT feelings of competence and social relatedness in combination with a sense of autonomy (defined as basic psychological needs) are important facilitators for intrinsic motivation to occur, to maintain and to enhance.

Externally motivated learning refers to learning that is a means to an end, and not engaged for its own sake. In contrast to classical theories of motivation that regard extrinsic motivation as a single construct, SDT proposes that extrinsic motivation is a construct with different facets that vary greatly with the degree to which the learner is autonomous (Deci & Ryan, 1985; Ryan & Deci, 2000). That is, besides intrinsic motivation and a-motivation, SDT distinguishes four different forms of extrinsic motivation that constitute a motivational continuum reflecting an increasing degree of self-determined behaviour, namely external regulation, introjection, identification and integration (Ryan & Deci, 2000).

10.2.3 Study 3 Open SNA approach with follow-up in-class discussion

10.2.3.1 Context and setting

The way teachers build relations and network with fellow colleagues and people outside their teaching and learning environment has been found to substantially influence their Academic Development (AD). For example, research in the context of primary school teachers in Portugal, the Netherlands and the US have provided robust and reliable evidence that social networks have a strong impact on trust (Coburn & Russell, 2008), collective efficacy (Moolenaar, Sleegers, & Daly, 2012), sharing of lesson materials (de Lima, 2007), teacher involvement in shared decision-making (Daly, Moolenaar, Bolivar, & Burke, 2010; de Lima, 2007), and schools' innovative climate (Daly & Finnigan, 2010; Daly et al., 2010). Furthermore, there is an emerging body of research that has found that social networks of teachers are also important in secondary and higher education (Rienties & Kinchin, 2014; Roxå & Mårtensson, 2009; Thomas, Tuytens, Devos, Kelchtermans, & Vanderlinde, 2019; Van Waes, Van de Bossche, Moolenaar, De Maeyer, & Van Petegem, 2015).

For example, Roxå and Mårtensson (2009) found that most academics discussed their teaching experience and reflections with a limited number of (mutually trusted) colleagues with whom they reciprocate the sharing of each other's knowledge in a private setting. Using longitudinal modelling, Van Waes et al. (2015) found that most academics maintained primarily relations with colleagues, while only incidental relations were built within the AD. In contrast, Rienties and Kinchin (2014) found that academics maintained on average four links with other academics in an interdisciplinary AD programme. Furthermore, academics maintained on average three contacts outside their AD to discuss their teaching practice. Therefore, Rienties and Kinchin (2014) argue that these interactions may have an impact on AD within and beyond the classroom.

Therefore, in Study 3 we reviewed the use of so-called open-SNA approaches with follow-up qualitative approaches amongst 114 academics from four faculties from a UK university participated in an 18 month AD programme (Rienties & Hosein, 2015; Rienties & Kinchin, 2014) in 2011-2012. In contrast to traditional, workshop-based AD accredited programmes often taken by early-career academics in the UK, where participants typically follow a "pre-described" programme with a bi-weekly two hour session on topic A, B, C (Parsons, Hill, Holland, & Willis, 2012), this AD programme used a distinct approach starting from the academics' daily practice and reflected on the educational problems academics may face (Rienties & Kinchin, 2014). During the first module, participants worked together on these educational problems in small-groups consisting of four or five members, using principles of inquiry-based learning (Rienties & Hosein, 2015; Rienties & Kinchin, 2014). The meeting times and setting for each small group were negotiated with the tutor. As a primary learning objective, participants were expected to develop greater understanding of their role as an academic within the learning environment. With an estimated workload of 150 hours per module, the majority of hours were self-study, as only five face-to-face meetings of two-three hours with an academic developer were arranged per module. During the third and fourth module, participants conducted an individual piece of action research within their own teaching practice.

As indicated by Rienties and Hosein (2015), participants were from 23 different departments, primarily from business (14%), engineering, hospitality & tourism (both 11%), mathematics (7%), psychology and biosciences (both 6%). The majority of participants were within the first year and half of their contract at the university as it is a contractual obligation to follow the AD programme. This meant the participants were not familiar with most of the other participants except for those perhaps in their own respective discipline.

10.2.3.2. Instruments used

After the initial nine months, we conducted both a closed-network analysis in combination with an open-network approach. First, we used a closed-network analysis technique (Daly et al., 2010; Rienties & Kinchin, 2014) after participants had worked together for nine months, whereby lists with names of the 54 and 60 participants were provided. Participants answered three Social Network questions, namely “In the AD programme, I have learned from...”, “I have worked a lot with ...” and “I am friends with ...” in a check-box manner.

Second, we asked participants using an open-network approach (Daly et al., 2010; Rienties & Kinchin, 2014) the following: “In addition to members of the [AD] programme, we are interested to know with whom you discuss your learning and teaching issues (e.g., how to prepare for a lecture, how to create an assessment, how to provide feedback). This could for example be with a colleague, a friend, family, or partner who is not following the [AD] programme.” Participants were asked the name of each network contact, the frequency of contact (as proxy for strength of tie), the type of relation, and where each contact works. A response rate of 88% was established for the open and closed SNA questions. Overall, the response rate for both types of data was 88%. The network data was cleaned and prepared using UCINET (Borgatti et al., 2002); Netdraw (Borgatti, 2002) was used to visualize the network and calculate basic key metrics.

10.2.3.3 Qualitative follow-up reflection exercise

In order to gain more insights the complex nature of the underlying relationships, we triangulated the SNA data (Crossley, 2010; Daly & Finnigan, 2010). One month after the SNA questionnaire was distributed, we presented the results in the form of three social network graphs (i.e., learning & friendship network of AD, external network) during one of four face-to-face sessions, which were attended by 45 and 32 participants respectively. This took the form of showing a set of social network graphs, which participants were asked to individually reflect on. As indicated by Rienties and Hosein (2015), participants were asked to reflect individually on the social network graphs for about ten minutes using predefined questions (e.g., what is the first thing that comes to mind when looking at these networks?; Why do you choose these persons to talk to (and not others)?; To what extent is it challenging to work with people from different disciplines?; In hindsight, would you have chosen the same group members?). Afterwards, the exercise was repeated in pairs and then as a facilitated discussion within the entire group. The verbal responses of 77 participants were recorded and transcribed, and 37 out of 77 (48%) participants who attended the follow-up session were willing to share these reflections (Rienties & Hosein, 2015).

10.3 Results

In order to explore the affordances and limitations of MMSNA approaches, we first explored what other researchers have published in this field using a systematic literature review in Study 1. Afterwards, we used two own exemplars (Rienties, 2019) of how we used MMSNA ourselves to explore what we have learned using MMSNA in practice.

10.3.1 Study 1 Systematic literature review

As indicated by Froehlich (2019), we were able to identify 44 studies that met our search criteria, which used in total 32 research methods. In **Fig. 10.1** the quantitatively-oriented methods are coloured white, while the qualitatively-oriented methods are coloured grey. As visible in **Fig. 10.1**, network surveys are being used as the most prominent type of data collection of the investigated MMSNA studies.

Fig. 10.1. Visualisation of MMSNA studies reviewed

One often used MMSNA research design included the sequential use of network surveys that are being analysed quantitatively, followed by a qualitative exploration using semi-structured interviews and some type of qualitative analysis (e.g., thematic analysis). For example, this approach was followed by Pifer (2011) when researching intersectionality in institutional contexts. Also, Rienties et al. (2015) made use of this approach for studying intercultural learning relations, whereby international students made conscious and deliberate decisions how to network with other international and host-national students. From the interviews with five case-study participants it became clear that cultural sensitivity, motivation to do well, willingness to share with others, and respecting others were crucial elements why some international students became cross-cultural bridge builders, while others did not (Rienties et al., 2015).

Parallel research designs were found in the data, too. For instance, the dissertation of Hiltz-Hymes (2011) used interviews and network surveys (and the associated subsequent analyses) in parallel. Similarly, Sarazin (2019) used a mix of interviews, notes, and ethnographic approaches as well as SNA to explore how school children in a disadvantaged background made use of their formal and informal friendship networks. This way, the findings of thematic analyses can be compared and triangulated with basic network measures and the results of an MRQAP analysis. In a longitudinal study of 10 beginning teachers in a range of primary schools, Thomas et al. (2019) explored how these teachers used their social networks within schools over time, and how they reflected on their experiences using three separate interviews.

The weighted nodal degrees (d) showed a clear separation between methods being used, including basic network metrics ($d = 72$), sociometric surveys ($d = 67$), and semi-structured interviews ($d = 63$), as featured, among others, in Froehlich, Mamas, et al. (2019). Overall, our systematic review of 44 MMSNA studies identified a diverse, wide-spread, and rich practice of using different MMSNA approaches. The generated map of methods allows for the differentiation of often-used combinations of methods and the “paths” less travelled by MMSNA researchers. These paths visualised in **Fig. 10.1** are important starting points for researchers who are considering to potentially use MMSNA to make sense of the world. In other words, MMSNA researchers may use **Fig. 10.1** to navigate the complex field of methods within SNA. Given that MM in general, and MMSNA in particular, draw their concepts and methods from a range of disciplines and ways of thinking, this is a daunting task and deserves attention (Frels, Newman, & Newman, 2015). MMSNA researchers need to be able to apply an array of both quantitative and qualitative methods of data collection and data analysis and take care of the sound integration of both. While some archetypes of MM have been developed in social science research about this approach (e.g., parallel designs, sequential designs, etc.), these archetypical solutions may be too abstract for the novice MM researcher.

While some approaches were more commonly combined than others, it would be impossible to argue that the best approach to answer a particular research question is by combining method X with method Y. Nonetheless, we argue that **Fig. 10.1** may be a useful tool for MMSNA researchers by highlighting common combinations of approaches. In the remainder of this chapter, we will provide two example studies that have combined different quantitative and qualitative approaches to objective (Study 2) and subjective (Study 3) SNA data.

10.3.2 Study 2 Objective SNA with content analysis

As illustrated in **Fig. 10.2**, we extracted interaction data from participants who used discussion forums to discuss complex problems in Economics. The discussion board was an integrated tool developed by Maastricht University, which provided a more scaffolded approach of interaction in comparison to the standard discussion forum tool in Blackboard at the time (Rehm et al., 2015; Rienties, Giesbers, et al., 2012; Rienties et al., 2009; Rienties et al., 2006). These discussion messages were afterwards coded by the three independent coders, which assigned the respective Veerman and Veldhuis-Diermanse (2001) codes to these messages. As these quantitative SNA data and qualitative data were collected simultaneously, we argue in line with **Fig. 10.1** that this is a parallel design. To illustrate the power of mixing objective SNA data with this content analysis data in understanding the interaction of contributions of individuals, the social network of all discourse activity (**Fig. 10.2**) as well as only higher cognitive discourse (**Fig. 10.3**) of one team are illustrated.

COURSES > ECONOMICS ONLINE SUMMER COURSE 3 (4-OSCE3-0505) > POLARIS KNOWLEDGE BUILDER > FORUM: INTRO TO TASK 1 (CLOSED)									
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Start new Thread	Enter thread	Questions and Answers	References	Remove	User Statistics	Item Statistics		Search	
Forum: Intro to Task 1 (closed)									
Subject	Author	Date	?	!	↑	&	⊙	🔍	#
☐ Summary of LG2	Jonas	21-07-06 16:03						⊙	0
☐ Summary of LG 1	Jonas	21-07-06 16:02						⊙	0
☐ Ways to tackle each task	Teacher 3	20-07-06 11:42	■					⊙	0
☐ LG 2: How do they interact, what is their role in the market?	Teacher 1	18-07-06 10:44						⊙	3
☐ Little example	Jonas	18-07-06 15:18						⊙	1
☐ remark and questions about the story	Teacher 3	19-07-06 10:29	■			▲		⊙	0
☐ "because the producer knows the beer is tasty, he...	Jonas	19-07-06 12:04			▼			⊙	0
☐ More actors	Jonas	20-07-06 12:22				▲		⊙	1
☐ Picture	Jonas	20-07-06 12:28				▲	+	⊙	0
☐ different markets	Bernard	20-07-06 13:53	■					⊙	1
☐ Can producer also be consumer?	Felix	20-07-06 14:14			◆			⊙	0
☐ consumer & producer	Teacher 4	26-07-06 10:04						⊙	0
☐ According to Dominique Waterval	Jonas	20-07-06 16:10			▼			⊙	1
☐ so?	Teacher 4	26-07-06 10:05						⊙	0
☐ different approach	Philipp	20-07-06 14:12	■					⊙	1
☐ ideas about the government	Paul	22-07-06 18:39			◆		▲	⊙	7
☐ Good.	Teacher 4	26-07-06 10:06						⊙	0
☐ more influence by government?	Jonathan	26-07-06 21:01						⊙	0
☐ LG 1: What are the main players in our market economy?	Teacher 1	18-07-06 10:43						⊙	2
☐ Producer-Consumer	Jonas	18-07-06 14:53	■				▲	⊙	0
☐ government role	Philipp	18-07-06 17:08					▲	⊙	2
☐ Government role	Teacher 3	19-07-06 10:33					▲	⊙	0
☐ other players?	Paul	22-07-06 18:56			▼			⊙	0
☐ predictable things	Veronica	24-07-06 17:17	■					⊙	0

Fig. 10.2. Discussion forum interactions in online summer course

First, using the Netdraw visualization tool in UCINET (Borgatti, 2002) the social networks visualized with whom individuals were communicating and whether the

connection was bilateral. The social networks illustrate to whom a learner (i.e., a red node) was communicating with, and what the direction of communication was. For example, Peter and Caroline had a so-called “reciprocal” link on the right side of **Fig. 10.3**, as they reacted both to each other’s contribution, and the arrow goes in both directions (Hanneman & Riddle, 2005; Scott, 2012). All learners, except Michael, were connected in discourse in this online summer course. However, Peter and Caroline did not have any direct link when looking at higher cognitive discourse in. Moreover, as shown in **Fig. 10.4**, we were able to show that their interaction was primarily on a lower cognitive level.

Fig. 10.3. Social Network of all discourse activity. Source: Rienties et al. (2009)

Second, some learners, like Veronica and Jonas, were central in **Fig. 10.3**, while others, like Jonas and Paul but not Veronica, were relatively central in the higher cognitive network of **Fig. 10.4**. In other words, not every learner (e.g., Veronica) who was central in the overall network (**Fig. 10.3**) was also central in the higher cognitive network (**Fig. 10.4**). Other learners (e.g., Paul) who were not necessarily central in the overall network became a central contributor to higher cognitive discourse. Indeed, as found by Rienties et al. (2009) on average in the course the learners contributed 25.64 (SD= 28.07) messages and there are substantial differences amongst individuals with respect to the amount of discourse as assessed by a Chi-Square test (χ^2 (df= 81 N=82) 2258.17, $p < .001$). In addition, if we distinguish between task- and non-task related discourse, again significant differences are found.

Furthermore, several learners, including Bart, Elena, Felix, and Michael, were not present in conversations on a higher cognitive discourse. This does not mean that they were not learning from these higher cognitive discussion forum messages as they could read and “digest” these interactions, but at least they were not actively contributing to these discourses. Hence, by integrating content analysis with SNA, we were able to distinguish multi-layered interaction patterns among learners based upon the type of discourse.

Fig. 10.4. Social Network of all discourse activity. Source: Rienties et al. (2009)

By using an integrated social network analysis, a detailed picture of the role of motivation on learning interaction processes can be established when comparing **Fig. 10.3** with **Fig. 10.4**. All three aspects of intrinsic motivation (Intrinsic Motivation to Know (IMTK); Intrinsic Motivation to Accomplish (IMTA); Intrinsic Motivation to Experience Stimulation (IMES)) were positively correlated with the three centrality measures from our social network analysis (Size, Task-related Size, and Higher Cognitive Size): see **Table 10.1**. What is particularly interesting that the rhos for task-related and higher-cognitive related discourse become larger relative to overall discourse for intrinsically motivated students. This implies that highly intrinsically motivated students distinguished themselves (much stronger) from extrinsically (identified regulation (EMID)),

introjected regulation (EMIN), and external regulation (EMER)) and amotivated students (AMOT), also with respect to their position in the network. Especially students with high levels of intrinsic motivation to know are central contributors to overall discourse (Reply Degree) (IMTK $r=0.24$, $p < .05$). Those students are also more central in task-related discourse (IMTK $r=0.27$, $p < .05$) and in contributions of higher cognitive discourse (IMTK $r=0.27$; IMTA $r=0.24$, $p < .05$).

Table. 10.1. Centrality, ego-density and academic motivation. Source: Rienties et al. (2009)

	IMTK	IMTA	IMES	EMID	EMIN	EMER	AMOT
<i>Social Network Analysis</i>							
Reply Degree	0.23*	0.21	0.18	0.00	0.00	-0.03	0.05
Reply TR Degree	0.27*	0.21	0.18	0.01	-0.04	-0.07	-0.12
Reply HC Degree	0.27*	0.24*	0.20	0.11	0.06	0.05	-0.16
Size	0.24*	0.21	0.22	-0.01	0.04	0.05	-0.02
TR Size	0.29*	0.26*	0.23*	-0.02	0.05	-0.03	-0.08
HC Size	0.29*	0.29*	0.24*	0.13	0.05	0.04	-0.12

*Correlation is significant at the 0.05 level (2-tailed).

This implies that highly intrinsically motivated learners both show up in the centre of the network but also on the outer fringe, but then as learners who have above average connections to other learners. Students who are highly extrinsically motivated do not distinguish from the average student in our online setting. The number of links of highly extrinsically motivated learners is on average. A-motivation demonstrates a negative but non-significant relationship with higher cognitive centrality ($r=-0.16$, n.s.) and higher cognitive size ($r=-0.12$, n.s.).

In other words, the results from the “objective” parallel MMSNA Study 2 show that individuals’ motivation can affect their participation in online discussion fora (Rienties et al., 2009). Some learners became active contributors to discourse, while other learners contributed only a limited amount to discourse. Although these results have already been found in other studies, this study was the first to empirically investigate how motivation can explain differences in quantity and quality of individuals’ online contributions. Hence, by employing MMSNA, we were able to unveil complex, and often hidden, social interactions between learners, that perhaps may not have been visible when just looking quantitatively at the number of posted messages, or qualitatively just on what participants were posting.

10.3.3.1 Lessons learned

Study 2 is one of the most cited studies in CSCL using SNA (Cela et al., 2015; Dado & Bodemer, 2017), and has encouraged researchers to look beyond pure SNA data to aim

to understand what participants are actually talking about, and why (Bogler, Caspi, & Roccas, 2013; De Laat & Schreurs, 2013; Giesbers et al., 2013, 2014; Kirschner & Erkens, 2013). Yet, the content analysis constituted a substantial amount of work. Consequently, one can wonder whether a simple closed network survey at the end of the module with a question like “from whom have you learned the most about economics during this online summer course” might have been easier. Moreover, follow-up interviews, incorporating the SNA results, might have provided an additional, interesting perspective.

Another reflection is that increasingly students will be using other social media technologies to interact with each other. When we conducted these studies in 2005/2006, Facebook and WhatsApp did not exist, and many students did not have smart phones (Clough, Jones, McAndrew, & Scanlon, 2008; Dillenbourg et al., 2011). Therefore, in order to share experiences and learn from each other, they had to connect to the university’s Virtual Learning Environment (VLE). With the rise of Web 2.0 tools like Facebook (Ellison, Steinfield, & Lampe, 2007; Madge, Meek, Wellens, & Hooley, 2009; Rienties, Tempelaar, Pinckaers, Giesbers, & Lichel, 2012; Sharples et al., 2016; Sharples et al., 2013), Twitter (Colleoni, Rozza, & Arvidsson, 2014; Rehm & Cornelissen, 2019; Rehm & Notten, 2016), Whatsapp (Madge et al., 2019), Wikipedia (De Wever, Van Keer, Schellens, & Valcke, 2011; Klein & Konieczny, 2015; Rehm et al., 2018; Sharples et al., 2015), and Youtube (Duffy, 2008; Holmes, Clark, Burt, & Rienties, 2013; T. Jones & Cuthrell, 2011) obviously students will increasingly learn outside the formal boundaries of the institutional VLE (Johnson et al., 2016; Law & Jelfs, 2016; Okada & Moreira, 2008; Roberts, Daly, Held, & Lyle, 2017; Watson, Watson, & Reigeluth, 2015). Several authors refer to this notion as ubiquitous learning (Cárdenas-Robledo & Peña-Ayala, 2018; Lally, Sharples, Tracy, Bertram, & Masters, 2012; Zhang, 2015), whereby students and staff have access to technology and information 24/7. For example, a wealth of studies on use of Facebook (Kirschner, 2015; Kirschner & Karpinski, 2010; Manca & Ranieri, 2013) have found that many students spent more time on Facebook than they do in the institutional’s VLE.

Given the omnipresence of knowledge and information on the web (Bråten, Strømsø, & Salmerón, 2011; Ferguson et al., 2017; Knight et al., 2017; Sharples et al., 2014) and the ubiquitous presence of technology for learning (Cárdenas-Robledo & Peña-Ayala, 2018; Lally et al., 2012; Zhang, 2015), one wonders whether conducting the same study again whether similar results would be found. One way to measure these informal networks is to extract and link Web 2.0 data with the VLE data using learning analytics approaches (Peña-Ayala et al., 2017; Peña-Ayala, 2018; Tempelaar, Rienties, & Giesbers, 2015; Tempelaar, Rienties, Mittelmeier, & Nguyen, 2018). However, the linking of various data sources might be technically complex, given that learners might use different user profiles, lack of interoperability between these systems (Conde, García, Rodríguez-Conde, Alier, & García-Holgado, 2014; Ferguson et al., 2016), and perhaps more importantly the interconnections between these systems might lead to strong ethical issues and undesired consequences (boyd & Crawford, 2012; Buchanan, 2011; Hoel, Griffiths, & Chen, 2017; Korir, Mittelmeier, & Rienties, 2019; Lally et al., 2012; Prinsloo & Slade, 2017). For example, the Open University UK has specifically excluded Web 2.0 tools like Facebook and Twitter as safe spaces for students, whereby learning analytics models will not take into consideration what students are saying or

doing in these spaces (Open University UK, 2014). Other institutions do take into consideration how students are sharing their concerns and issues in Web 2.0 tools like Facebook in order to support their wellbeing (Ferguson et al., 2016; Hartrey, Denieffe, & Wells, 2017; E. Jones, Samra, & Lucassen, 2018; Piper & Emmanuel, 2019).

One way to address how knowledge and information is shared in these informal and social media spaces could be to combine objective SNA data extracted from the VLE with self-reported SNA data from students. To a certain degree, it does not really matter if students are sharing nodes, information, or ideas (Hommes et al., 2014; Hommes et al., 2012) using the VLE, or using informal social media tools, as long as they are able to work effectively together. These informal data points could be collated by researchers using self-reported closed or open SNA approaches. Researchers will need to balance when, what, and how often participants are asked to complete these self-reported instruments, and whether it may be more appropriate to use qualitative follow-up approaches to explore the lived experiences of these students.

10.3.3 Study 3 Open SNA approach with follow-up in-class discussion

In our Study 3 of 114 academics working in an Academic Development (AD) programme, we employed a sequential design whereby we first collected quantitative self-reported SNA data with follow-up in-class discussions of the results by participants one month after the quantitative data was collected. The results indicated that most academics developed cohesive links, either within their own assigned group or within the wider AD programme after nine months. As illustrated in **Table 10.2**, on average participants developed 3.09 friendship relations within the AD programme. 1.07 friendships were based upon the initial group division during the first module, when participants were assigned to work in smaller groups of 4-5 participants. 2.02 of their self-reported friendship relations were based outside their first group and can be characterised as informal ties. Participants had on average 4.84 learning and teaching relations within the AD programme, of which 2.30 were based upon the initial group division.

Second, as illustrated in **Fig. 10.5**, while some academics were centrally positioned, others were less connected and positioned towards the fringes of the network. The colour and shape of the node represents the respective faculty of each participant, while the number of the node referred to the respective group an academic was enrolled in the AD programme. Note that the visualisation software tool Netdraw (Borgatti, 2002) positions the academics at random across the X- and Y-axis based upon the (perceived) social interactions between academics, whereby academics who share similar connections are positioned more closely together (Rienties & Kinchin, 2014). Being on the left of the graph is not necessarily better or worse than being on the right, top or bottom, but academics with similar connections are positioned closer together.

As illustrated by links between nodes with different colours and shapes in **Fig. 10.5**, most academics developed a range of interdisciplinary learning relations with other academics. For example, on the left of **Fig. 10.5**, four members (each from a different faculty) of group 22 were connected to each other, while on the left of **Fig. 10.5** five members of group 35 (three from arts and social science faculty, two from other faculties) were connected to each other. MMSNA researchers could use these SNA visualisations to identify how cohesive the learning climates within groups are. For

example, it would perhaps be interesting to know why members of group 29 were often not connected to their group.

Table 10.2. Social ties within and outside groups/academic development.
Source: Rienties and Hosein (2015)

SNA metric	M	SD	Range
Friendship within group	1.07	1.23	(0-4)
Friendship within AD	3.09	1.97	(0-10)
Work relations within group	2.37	1.29	(0-4)
Work relations within AD	4.84	2.22	(1-11)
Learning within group	2.30	1.36	(0-4)
Learning within AD	4.84	2.43	(0-15)
Learning outside AD	3.17	2.31	(0-10)
Same discipline	2.39	2.06	(0-8)
Externals outside the institution	0.94	1.11	(0-4)

As illustrated in **Fig. 10.6**, the learning and teaching network of the two cohorts and their external network contacts were rather diverse. The grey and black colour in **Fig. 10.6** indicated the participants in the AD programmes (Rienties & Hosein, 2015), while the white nodes were the so-called external relations of the AD participants. In total 293 network contacts outside the AD were used to discuss learning and teaching issues with the 114 AD participants (Rienties & Hosein, 2015). 92 (81%) participants indicated they discussed their learning and teaching practice with external relations. Although the visualisation is complex, These open network approaches allow MMSNA researchers to map and analyse the informal social relations outside the academic development programme. **Fig. 10.6** highlights the intensity of the usage of the informal network outside the AD programme for most participants, whereby participants of the second cohort also learned from the experiences of the first cohort (Rienties & Hosein, 2015).

From the open-coding of the qualitative data of the completed forms, transcripts of the discussions, and reflections by the facilitators, three broad thematic areas could be identified. More specifically, the data suggest professional, emotional and academic support as being relevant for the case at hand. Participants were in need for sparing partners, with whom they could talk about their feelings, challenges and frustrations (Rienties & Hosein, 2015; Rienties & Kinchin, 2014).

Fig. 10.5. Learning & teaching network after nine months.

Fig. 10.6. External and internal learning and teaching network.

10.3.3.1 Lessons learned

Extending beyond the boundaries of the closed networks and also including open networks definitely contributed to a more refined understanding of how people learned within and outside their academic development programme. Whether or not these external relations were developed using formal networks (Moolenaar, 2012; Roxå & Mårtensson, 2009; Van Waes, De Maeyer, Moolenaar, Van Petegem, & Van den Bossche, 2018) or informal social media networks (Cárdenas-Robledo & Peña-Ayala, 2018; Rehm & Cornelissen, 2019; Rehm et al., 2018; Rehm & Notten, 2016; Rienties & Kinchin, 2014), many academics indicated that these networks were very useful “to keep them sane”. Furthermore, organizing a reflection meeting one month after the SNA data certainly added another relevant dimension to the question of why and how participants networked in and outside the formal programme. Nonetheless, while the open SNA approach, as well as the data triangulation can be considered as a methodological improvement, we would like to highlight two points of caution.

First, the open network approach quickly became troublesome to organize and codify, due to a wide variety of possible answers (e.g. “my wife”, “my colleagues in my department”, “John”). Linked to the previous study, whether it is ethical to involve people who were not consulted can be debated (Korir et al., 2019; Lally et al., 2012). Second, the data might have been subject to a biased sample. What we mean by this is that participants were academics and researchers themselves, which likely influenced their willingness to partake in the study and learn from the results. It remains to be seen

if this approach also works with other target audiences, such as younger participants, or participants who cannot be easily followed over a longer period of time. However, the research by Rehm and Cornelissen (2019) does highlight that when done carefully, triangulating large open (Twitter) networks with in-depth interviews could work under certain circumstances.

10.4 Discussion

An increasing number of researchers are using and integrating other social science approaches in conjunction with Social Network Analysis (SNA), as indicated by a range of reviews of SNA studies (Borgatti & Halgin, 2011; Borgatti et al., 2009; Carpenter et al., 2012), and in education (Golonka et al., 2014; McConnell et al., 2012; Van den Bossche & Segers, 2013; Vera & Schupp, 2006), and CSCL and SNA in particular (Cela et al., 2015; Dado & Bodemer, 2017). In this Chapter we first provided a systematic review of Mixed Method Social Network Studies (MMSNA), where we identified 44 studies that mixed qualitative approaches with SNA approaches. Secondly, we provided two MMSNA studies exemplars from our own practice how such studies could be applied and evaluated.

10.4.1 Study 1

Building on Froehlich (2019) our systematic review allowed for a more nuanced description of MM research designs. Applying social network thinking to MM research gives us a new dictionary from which to discuss research designs. **Fig. 10.1.** is an estimate of what methods are relatively more used than others in MMSNA designs. These methods of data collection may be interpreted as methods that integrate previous analyses; where one strand of research merges into another. In other words, the generated map of methods allows for the differentiation of often-used combinations of methods and the “paths” less travelled. This is important to inspire new ways of making sense of the world.

Given the complexity of adopting and mixing the various quantitative and qualitative approaches in MMSNA in various sequential cycles (e.g., first quantitative self-report SNA, follow-up semi-structured interviews, alternatively start with semi-structured interviews and afterwards longitudinal self-reported SNA), theoretically there could be a near infinite number of potential combinations of implementing MMSNA. As a result, providing a clear 1-2-3 step guideline of implementing MMSNA may be undesirable, or perhaps unrealistic. Nonetheless, one approach that could bear fruit is to learn from researchers who have already implemented a particular MMSNA approach, and learn, build on their lessons-learned. In other words, we encourage researchers and practitioners to use **Fig 10.1** to find whether there are potentially compatible designs, read up on these respective studies as identified by Froehlich (2019), and explore how these researchers have implemented their respective designs.

10.4.2 Study 2

Whatever MMSNA method one adopts, we have to be mindful that the interpretation of these networks and related data are just our unique interpretations of reality, which are strongly influenced by our own lenses and perspectives (Hesse-Biber, 2010; Kadushin, 2005; Korir et al., 2019; Prinsloo & Slade, 2017; Sarazin, 2019; Schoonenboom et al., 2018). As highlighted from Study 2, we were able to empirically determine that intrinsically motivated students were more likely to contribute to higher cognitive discourse than extrinsically motivated students (Rienties et al., 2012; Rienties et al., 2009). Nonetheless, there could be a myriad of reasons why these results could be different in another contexts, or even when the study would be replicated in 2020. For example, in many discussion forums participation is rather unequal, and dominated by certain participants (Rehm et al., 2015; Rehm et al., 2018). Indeed other researchers have found that gender (Bevelander & Page, 2011), ethnicity (Jindal-Snape & Rienties, 2016; Rienties et al., 2015), seniority (Rehm et al., 2015), and technology access (Gem-mell & Harrison, 2017) could be mediating factors in engagement, explaining a divergence of practice.

Furthermore, given the ubiquitous presence of technology (Cárdenas-Robledo & Peña-Ayala, 2018; Sharples et al., 2015) and the opportunities of learners to use both formal and informal learning tools (Clough et al., 2008; Duffy, 2008; Rehm & Notten, 2016), one wonders how MMSNA researchers need to effectively balance and integrate these different potentially rich data sources. As highlighted from our Study 2, there could be several ethical issues when combining different data sets. Furthermore, the lens of Study 2 was focussed on Self-Determination Theory (Deci & Ryan, 1985; Ryan & Deci, 2000; Vallerand et al., 1992) and motivation, while perhaps intersectionality with other factors like gender or ethnicity could be an important explanatory factor.

10.4.3 Study 3

In Study 3 we identified that many participants actively developed learning links within their Academic Development (AD) programme, while at the same time maintaining many links with “external” people outside the AD programme (Rienties & Hoesin, 2015; Rienties & Kinchin, 2014). For many participants these relations were maintained to keep them “sane”, and to rapport and reflect (up)on their professional, emotional, and academic support. As the lens of the research team was embedded into the AD programme, any other lenses in terms of intersectionality, like gender (Bevelander & Page, 2011), seniority (Rehm et al., 2015), or disciplinary differences (Rienties & Tempelaar, 2018), were not explored explicitly. As a result, researchers with different research questions and/or approaches could potentially find different patterns and results when conducting MMSNA.

Starting-out researchers may use **Fig. 10.1.** to navigate the complex field of methods within SNA. Given that MM in general, and MMSNA in particular, draw their concepts and methods from a range of disciplines and ways of thinking, this is a daunting task and deserves attention (Frels, Newman, & Newman, 2015). MM researchers need to be able to apply an array of both quantitative and qualitative methods of data collection and data analysis and take care of the sound integration of both. While some

archetypes of MM have been developed in general research about this approach (e.g., parallel designs, sequential designs, etc.), these archetypical solutions may be too abstract for the novice MM researcher. Furthermore, not all of these archetypes are applicable to our domain of interest, which is education and learning research.

The generated map of MMSNA is also a tool that contributes to the objective of making MMSNA more accessible for researchers less experienced in MM. This is achieved by moving away from typologies derived from theory that "have become almost too refined" (Bryman, 2006) and hence may be overly complex for novice researchers. Instead, as also evidenced in Study 2 and Study 3 we took an approach that is close to research practice (following Bryman, 2006), and that offers an innovative and intuitive way to understand the mixing of methods in the field of education and learning research.

10.5 Conclusions

First, the literature review indicates that the reporting practices of MMSNA studies may be improved. This is understandable, since the very notion of MMSNA is very new and it so far even lacked a coherent definition. Second, the sequencing of methods was often described in very imprecise terms, too. For example, Pifer (2011) writes that she "completed a social network analysis, followed by in-depth one-on-one interviews"—however, this leaves out the step of quantitative analysis happening between these two data collection procedures that would tie the different strands of research together.

Third, the primary lesson we learned from writing the MMSNA book (Froehlich, Rehm, et al., 2019) is to continuously engage the stakeholders in the design, implementation, and evaluation of the research (De Laat & Lally, 2004; Hommes et al., 2014). By discussing initial trends and visualisations of SNA with the rich narratives from the qualitative approaches some interesting and unexpected findings emerged over time. At the same time, while great care was taken to code data with multiple coders, each with their own unique lenses, a major limitation of all three studies was that the interpretations of these findings were primarily reliant on the respective research teams. Future research should aim to not only triangulate quantitative SNA with other quantitative and qualitative data, but also to go back to the main stakeholders to determine whether (or not) the "emergent" findings resonate with the actual lived experiences of students, teachers, and senior management.

Fourth, as highlighted by the three studies there could be strong ethical concerns when gathering diverse and rich MMSNA data from various data sources. For example, participants who agree to participate in a piece of research in most social science approaches are able to do so in an anonymous and confidential format (Borgatti & Molina, 2003; Conway, 2014; Kadushin, 2005). Yet this is not the case in SNA, and as argued by Korir et al. (2019) in particular in MMSNA contexts there might even be stronger ethical concerns when researchers are able to link social media profiles of learners with learning processes and outcomes (Korir et al., 2019; Rehm & Cornelissen, 2019; Schoonenboom et al., 2018). As described in a review of ethics in SNA studies by Borgatti and Molina (2003, p. 338): 'the most obvious difference is that in a network study, anonymity at the data collection stage is not possible ... [as] the researcher must know who the respondent was to record a link from that respondent to the persons with

whom the respondent indicates having relationships.’ Yet, confidentiality of respondents’ identities are considered to be an essential part of ethics and privacy in social science research (boyd & Crawford, 2012; Buchanan, 2011; Hoel et al., 2017; Korir et al., 2019; Lally et al., 2012; Prinsloo & Slade, 2017) and (MM)SNA research in particular (Kadushin, 2005; Korir et al., 2019). Therefore, as argued by Korir et al. (2019) strong procedures and policies are needed in SNA studies to ensure that, during the data processing phase, the researcher acts as an independent gatekeeper between respondents and potential end-users of social network data (i.e., peers within the social network, managers making promotion and firing decisions, teachers addressing potential drop-out issues, other researchers).

For example, in Study 3 we informed participants at the start of the study of the main purpose of the study (i.e., informed consent), and the options not to participate (i.e., right to be excluded). Practically, participants could hand in their responses anonymously if they desired by putting their responses in an envelope. Furthermore, if participants did not want to share their responses at all, this was also feasible. Finally, any concerns by participants could be shared with the main researcher or by contacting an independent third-party by the information sheet provided separately in the informed consent and subsequent “report” shared with participants. In other words, in line with common ethics practices we encourage MMSNA researchers to be transparent and open about the purpose of the MMSNA study to all recruits and participants. This is particularly important given the opportunities to connect and triangulate data of people who have opted not to join the research (Borgatti & Molina, 2003; Crossley, 2010; Korir et al., 2019).

A particular concern for MMSNA research is the inclusion of students who have not indicated consent to participate in a piece of research. In SNA it is often still possible to generate a social network profile of a non-respondent based upon the perceived relations provided by others in the network (Conway, 2014; Kadushin, 2005), and in MMSNA in particular it can be relatively straightforward to identify a particular person when triangulating different forms of data, either from interviews (Froehlich & Brouwer, Forthcoming; Rienties, 2019; Sarazin, 2019; Schoonenboom et al., 2018; Thomas et al., 2019), or from social media data. Of course this leads to substantial and difficult ethical dilemmas for researchers to address, irrespective of whether particular student made a conscious (e.g., refusal to participate, fear of being marginalised) or unconscious decision (e.g., incomplete submission, forgot to indicate the respondent’s name, forgot to participate in online survey) to (not) participate. Therefore, Korir et al. (2019) encourage MMSNA researchers and practitioners should take into consideration the following three questions:

1. Are you going to report about the non-respondents?
2. Are you going to use non-respondents’ data in any way?
3. In this case while the participants do own their own perceptions, is it ethical to make any statements/inferences about non-respondents?

Overall, we hope that our chapter has contributed to an overview of the challenges and affordances of using MMSNA. When combining and integrating different forms of data and artefacts, there are several complex issues that researchers, practitioners, and managers need to take into consideration. As highlighted by Winston Churchill, success consists of going from failure to failure without loss of enthusiasm.

10.6 References

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