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Unravelling data use in teacher teams: How network patterns and interactive learning activities change across different data use phases

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H I G H L I G H T S

- Teachers' networks change across data use phases.
- Teachers' learning activities change across data use phases.
- Little interdependency in teachers' use of pupil learning outcome data.

A R T I C L E I N F O

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A B S T R A C T

Interactions among teachers are assumed to improve the quality of teachers' data use. Grouping teachers together challenges them to a more in-depth investigation of how pupil learning outcomes can be improved. This study combines social network analysis with qualitative data out of six teacher teams to provide insight into how teacher interactions change across data discussion, interpretation, diagnosis and action. We find that teachers' networks become smaller, and that interactions become more intense and interdependent when progressing through the different phases.

1. Introduction

Data use, and particularly teachers' use of pupil learning outcome data, has become an important topic in educational research. After all, different types of actions based upon data, such as a change in teaching strategies or differentiation, have potential benefits for student achievement (Campbell & Levin, 2008; Carlson, Borman, & Robinson, 2011). Researchers generally conceptualize data use as a cycle of sub-processes (Ciampa & Gallagher, 2016; Marsh & Farrell, 2015; Schildkamp, Poortman, & Handelzalts, 2016). The translation from raw data into knowledge and improvement actions is guided by the discussion and correct interpretation of data, diagnosis of problems and design and introduction of improvement actions (Verhaeghe, Vanhoof, Valcke, & Van Petegem, 2010). During these phases, teacher interactions are essential (Copland, 2003; Hubbard, Datnow, & Pruyn, 2014). A variety of knowledge and skills is required to accomplish each of the data use phases, ranging from interpretation and analysing skills to advanced pedagogical knowledge (Gummer & Mandinach, 2015). Grouping teachers together to combine and share expertise challenges teacher groups to more thorough discussion and consideration of potential explanations for, for example, poor student results (Bertrand & Marsh, 2015). Therefore, embedding data use in social structures is assumed to result in better-considered instructional changes and provide teachers with opportunities to learn from one another (Van Gasse, Vanlommel, Vanhoof, & Van Petegem, 2016; Van Waes et al., 2016).

Although research has acknowledged the importance of the interactive and cyclical character of data use, there remain gaps in the literature with regard to both characteristics. First, in particular out of the niche of intervention studies, data use has been insufficiently approached as a cycle of sub-processes. Therefore, teachers' data use often remains a black box in research and little is known on changes in teacher behaviour throughout different data use

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phases (Little, 2012). Second, 'collaboration' is often used as a container concept to study teacher interactions. However, interactions can vary depending on lower or higher levels of interdependence in teachers' mutual activities (Little, 1990; Van Gasse et al., 2016; Van Waes et al., 2016). For example, teachers are not bound to changing their instruction when collaboration only involves data use discussion. This is different when teachers make arrangements in data use collaboration. Therefore, the granularity in the concept 'collaboration' needs to be better addressed (Bertrand & Marsh, 2015; Van Gasse, Vanlommel, Vanhoof, & Van Petegem, 2017). Approaching teachers' interactive activities on a continuum from lower to higher degrees of interdependence is a crucial step to better understand changes in teachers' interactive behaviour in the different phases of data use.

Examining teacher interactions during different data use phases is an essential contribution to the current knowledge base. Up to now, it remains unclear how a potentially supportive environment for a complex task such as data use is used by teachers. Insights into if and how teachers interact with colleagues are needed to generate knowledge on when and how individual expertise is (not) shared within teams. Extending our knowledge base in this regard is crucial bearing in mind the benefits of teacher interactions for data-based instructional change (Bertrand & Marsh, 2015).

The general aim of this study is to unravel how teacher interactions change across the data use cycle. To do so, we distinguish between structural interaction patterns and interactive activities of teachers. Structural interaction patterns are investigated by means of social network analysis. In this method, the information of both actors involved in interactions is combined. Therefore, social network is powerful to unravel teacher interactions in more detail compared to, for example, survey or interview research that investigate collaboration through general questions.

The structural patterns in themselves provide binary information on the (non-) presence of interactions and not on what exactly happens when people interact (Baker-Doyle, 2015; Mohrman, Tenkasi, & Mohrman, 2003). Therefore, social network analysis is complemented by interviews with teachers to provide insights into interactive activities that provide teachers with learning opportunities (i.e., interactive learning activities) and are embedded within the structural patterns determined. The Little (1990) framework is used to address the granularity in these activities by means of the level of interdependency. Four types of interactive learning activities are distinguished: daily conversations (storytelling), asking for help or advice (helping), sharing materials or strategies (sharing) and making arrangements or work groups (joint work).

Up to now, only few studies in the field of data use have drawn upon social network analysis. In combination with insights into teachers' interactive learning activities, this study provides a detailed picture on how the extent and the interdependency of teacher interactions change across the data use phases. Therefore, the contribution of this study can be found in both the methodological approach and the theoretical aim to expose the changes in teacher behaviour. To do so, two main research questions will guide this paper:

1. How do structural interaction patterns in teacher teams remain similar or change across data use discussion, interpretation, diagnosis and action?
2. Which interactive learning activities are embedded in the structural patterns of teacher networks?

2. Conceptual framework

To situate data use interactions in a broader context, we first describe the conceptualization of data use and data in this study. Subsequently, characteristics of structural interaction patterns and interactive learning activities will be discussed.

2.1. Data use and data

Data use is a way of inquiry-based process monitoring and problem solving in schools. The central idea is that the analysis and interpretation of different types of data is powerful to guide practitioners in instructional and school improvement (Campbell & Levin, 2008; Carlson et al., 2011).

The description of diverse data use practices has shown the merit of data use that follows a cycle of sub-processes (Ciampa & Gallagher, 2016; Marsh & Farrell, 2015; Schildkamp et al., 2016). To transform raw data into information and actionable knowledge, a variety in knowledge and skills is needed (Gummer & Mandinach, 2015; Marsh & Farrell, 2015). Approaching data use as an inquiry circle, can guide teachers to accomplish the translation from data into meaningful decisions (Marsh, Bertrand, & Huguet, 2015). This increases the quality of teachers' data use, because the tendency to jump from data to improvement actions without in-depth consideration of potential causes and alternatives is interrupted (Hubers et al., 2017; Schildkamp et al., 2016). Therefore, the approach to data use as a cyclical process is essential in order to expand and refine the knowledge as to how teachers use data to improve educational processes.

In a lot of research, data use phases of discussion, analysis, interpretation and action are distinguished (Gummer & Mandinach, 2015; Marsh, 2012; Schildkamp et al., 2016). Nevertheless, given teachers' difficulties with the translation of data to classroom interventions (Datnow & Hubbard, 2016; Gummer & Mandinach, 2015), we use a conceptualization that explicitly inserts a phase of problem diagnosis. Therefore, in this study, data use is considered as a cyclic process in which phases of discussion, interpretation, diagnosis and action follow on from each other (Verhaeghe et al., 2010). First, data that guides educational decisions must be read and discussed. Second, data must be interpreted correctly. Third, a deliberation of potential causes and explanations is carried out in the diagnosing phase. Finally, improvement actions can be designed and implemented in teachers' classroom practice (Verhaeghe et al., 2010). Although these data use phases may seem linear and straightforward, the literature shows that data use cycles are often interrupted or that teachers return to previous phases (Marsh & Farrell, 2015; Schildkamp et al., 2016).

A great deal of successfully progressing through data use depends on the data that is used (Verhaeghe et al., 2010). This study reports on teachers' use of pupil learning outcome data. These data are generally seen as highly informative given their potential for improving teachers' practice and eventually pupils' achievement (Campbell & Levin, 2008; Carlson et al., 2011).

The use of pupil learning outcome data has been investigated in several studies (Jimerson, 2014). The concept is often delimited to cognitive output indicators, which in themselves fail to provide a complete picture of a pupil's learning (Schildkamp & Kuiper, 2010; Schildkamp, Rekers-Mombarg, & Harms, 2012). Therefore, our conceptualization of pupil learning outcome data includes cognitive outcomes (i.e. linguistic and arithmetic skills) as well as non-cognitive learning outcomes (i.e. attitudes, art and physical education). Additionally, both quantitative data (e.g. class tests) and qualitative data (e.g. observations) fit into our conceptualization.

2.2. Data use interactions

Teachers' data use benefits from interactions with colleagues

(Bertrand & Marsh, 2015; Copland, 2003; Hubbard et al., 2014). The different data use phases require variety complex knowledge and skills. Therefore, inadequate knowledge and skills of teachers can subvert data use (Datnow & Hubbard, 2016). Interactions are seen as a way to cope with teachers' individual pitfalls to data use (Hubbard et al., 2014; Mason, 2003). Grouping teachers together to combine their individual experiences, knowledge and skills challenges teachers to thorough discussion and consideration of potential explanations for, for example, poor student results (Bertrand & Marsh, 2015). Teachers' individual expertise is complemented and broadened by those of colleagues which can lead to instructional changes of higher quality. Social relations are not only assumed to improve the quality of teachers' data use, but embedding data use in social structures has been considered to provide teachers’ with valuable learning opportunities (Van Gasse et al., 2016; Van Waes et al., 2016).

Although the data use cycle of discussion, interpretation, diagnosis and action provides a clear guidance for teachers, differences in data use quality and results of the data use cycle have been determined (Hubers, Poortman, Schildkamp, Pieters, & Handelzalts, 2016; Schildkamp et al., 2016). For example, Schildkamp et al. (2016) found differences between teams regarding the use of higher level thinking skills throughout the data use phases. Additionally, according to Hubers et al. (2016), the same sequence can result in different knowledge gains in teams. This implies that the outcomes of data use may strongly depend on how people interact during the different phases. The quality and effectiveness of teachers’ data use can be determined by getting insight into teacher interactions (Bertrand & Marsh, 2015). Therefore, knowledge is needed about the interactions that take place during the different data use phases.

Based on the research questions, we distinguish between structural interaction patterns and interactive learning activities to describe the interactive component of the data use cycle. We examine structural interaction patterns drawing on social network theory. The central idea in social network theory is that the position of actors within a network determines their access to, for example, data use knowledge, strategies or skills (Finnigan & Daly, 2012). Structural interaction patterns are useful to determine the number of interactions in teams (Mohrman et al., 2003) and have demonstrated the importance of teacher interactions for different school improvement purposes (e.g. student achievement, reform, professional development) (Moolenaar, Sleegers, & Daly, 2012; Penuel, Riel, Krause, & Frank, 2009; Penuel, Sun, Frank, & Gallagher, 2012; Rienties & Kinchin, 2014).

2.2.1. Structural interaction patterns

Generally, there are three network characteristics to determine structural interaction patterns in teacher teams: density, reciprocity and centralization (Moolenaar, 2012).

Density refers to the cohesion within a network. The measure is calculated as the total number of actual ties in a network, divided by the total number of potential ties in a network (Borgatti, Everett, & Johnson, 2013; Carolan, 2014). Density provides an indication of the total activity of teachers within a network. In dense teams, teachers are more actively engaged. Therefore, resources (e.g. data use knowledge, strategies or skills) are moved more quickly than in sparse teams (Finnigan & Daly, 2012).

Reciprocity is a measure for mutual ties in networks (Borgatti et al., 2013; Carolan, 2014). Whether or not ties are reciprocated provides information on the depth of relations within a network. Reciprocated relations demonstrate more extensive interaction (Mohrman et al., 2003). Therefore, these relations provide quicker access to others’ resources (e.g. data use knowledge, strategies or skills) (Hansen, 2002; Mohrman et al., 2003) and opportunities for sharing complex information and knowledge (Kilduff & Tsai, 2003).

Centralization reflects the involvement of all team members in the network (Borgatti et al., 2013). For example, if a teacher team is highly centralized, a great number of colleagues will consult the same teacher (i.e. an expert-teacher). Depending on the team goal, a more centralized or decentralized structure may be found to be effective (Cummings & Cross, 2003; Daly & Finnigan, 2011; Sparrowe, Liden, Wayne, & Kraimer, 2001). With regard to data use, the involvement of many teachers in the process is generally seen as valuable to support thorough data use and learning opportunities in teacher teams (Keuning, Van Geel, Visscher, Fox, & Moolenaar, 2016).

To our knowledge, few studies have investigated teacher networks in the context of data use. Hubers et al. (2017) examined teacher networks on data sharing and discussing educational problems. Keuning et al. (2016) studied different data use discussion networks (i.e. discussing achievement goals, instructional strategies and problems). Both studies took place in an intervention setting in which data use was supported in schools. A study by Farley-Ripple and Buttram (2015) did not take place in an intervention setting and was slightly different because data advice networks were compared to teachers' regular professional network. Nevertheless, across the studies, similar conclusions were drawn. The networks were in all cases relatively sparse. Low density measures were found. Farley-Ripple and Buttram (2015) emphasized that the density measures of teachers' data use networks were low, compared to their regular professional network. Thus, limited interactions took place in the data use networks. Reciprocity measures were investigated in the studies of Hubers et al. (2017) and Keuning et al. (2016) and were also evaluated as being low. In other words, teachers did not tend to engage in deep interactions. Centralization was examined in all studies and identified as being moderate to high. Farley-Ripple and Buttram (2015) assessed the centralization measures of the data advice networks as being high compared to teachers’ professional network. This means that, across the studies, the tendency was that teachers consulted few expert colleagues for data use.

Although the aforementioned studies can tell us something about the structural interaction patterns to expect in data use networks (i.e. low density and reciprocity and high centralization measures), it is difficult to generalize these findings into assumptions for the present study. First, we will examine teacher networks outside an intervention setting. Because both the studies by Hubers et al. (2017) and Keuning et al. (2016) included data use support in schools, more teachers might have been engaged in data use than would be the case without the support provided. Second, the limited number of network studies in the context of data use do not provide insight into each of the data use phases. Since the data use cycle inherits different and complex skills in each phase, we expect different structural interaction patterns for discussion, interpretation, diagnosis and action. Insights into these differences are an essential contribution to the knowledge on how teachers use their networks when progressing through the data use cycle.

A lot of research has merely focused on structural interaction patterns to obtain insights into teacher interactions. However, deeper insights are reached when complementary evidence is provided about the interactions that are studied (Baker-Doyle, 2015; Mohrman et al., 2003). Insights into the ‘stories’ behind teachers' networks are useful to describe the actual activities within a network (Van Gasse et al., 2016; Van Waes et al., 2016). Therefore, additionally to the consideration of structural interaction patterns, we will describe the interactive learning activities in data use networks.

2.2.2. Interactive learning activities

In the data use literature, interactions among teachers are often described as collaboration. However, depending on the degree of interdependence in teachers' interactions, a more refined conceptualization is needed (Hammick, Freeth, Copperman, & Goodsmith, 2009; Van Gasse et al., 2017).

The Little (1990) framework is particularly useful in order to address the granularity in the 'collaboration' concept. Little (1990) categorizes types of interactions depending on their level of interdependency. Four types of interactive learning activities are distinguished: storytelling, helping, sharing and joint work.

In *storytelling* activities, teachers are nearly completely independent of one another. Teachers quickly exchange information through daily conversations. Whether or not this information is used depends completely on individuals (Little, 1990). In the context of data use, storytelling can include a range from general conversations about data use to topic-specific conversations (Bolhuis, Schildkamp, & Voogt, 2016; Datnow, Park, & Kennedy-Lewis, 2013).

In *helping* activities, individual teachers seek for help or advice. Subsequently, they decide independently to follow or ignore the help or advice that is offered (Little, 1990). Helping is less open ended on the side of the help-seeker compared to storytelling activities because of the underlying purpose of help-seeking. In the context of data use, a lot of emphasis has been laid on interactions because of the helping opportunities they offer (Datnow et al., 2013; Hubbard et al., 2014). Helping activities can be crucial in order to tackle personal barriers with regard to data use, such as difficulties with analysing and interpreting data or setting improvement actions (Datnow et al., 2013; Hubbard et al., 2014; Jimerson, 2014).

Sharing implies the distribution of data, materials and methods, or the open exchange of ideas and opinions (Little, 1990). Teachers take initiatives to make aspects of their work accessible for others, and to expose their materials, choices and rationales. Sharing implies a higher level of interdependence compared to storytelling and helping. Nevertheless, teachers are not bound to share strategies or materials with regard to how they shape their daily practice (Little, 1990). The concept of sharing is also validated in the context of data use. However, there is little insight into the frequency of sharing because of the great differences in sharing across studies (Bolhuis et al., 2016; Hubers et al., 2016; Katz & Earl, 2010; Kwakman, 2003).

Joint work are "encounters among teachers that rest on shared responsibility for the work of teaching". Joint work implies higher levels of interdependency in terms of collective purposes and collective action, such as work groups and agreements (Little, 1990). In general, limited evidence on joint work has been found (Katz & Earl, 2010; Kwakman, 2003; Van Gasse et al., 2016; Van Waes et al., 2016). In the context of data use, some studies report on joint work among teachers, but those are mainly intervention studies (Cosner, 2011; Hubers et al., 2016; Schildkamp et al., 2016).

3. Method

We used a mixed-method approach. The first research question, regarding the structural interaction patterns in the data use cycle was answered using social network analysis. For the second research question, regarding the interactive learning activities of teachers, a qualitative approach including semi-structured interviews was used. Before going into detail on the combination of both methods, we briefly describe the research context of this study.

3.1. Context of the study

The current study took place in secondary schools in Flanders that participated in a project on the assessment of pupils' writing competences. In Flanders, the government's perspective on data use is school improvement oriented. Schools are autonomous in how they achieve the standards that are defined at the end of the second and sixth grade of secondary education (Penninckx et al., 2011). Central exams and resulting public data bases or rankings of schools do not exist (OECD, 2013). Schools themselves have full responsibility for obtaining insight into attaining the Flemish standards at the end of secondary education. Because of the absence of standardised testing, schools and teachers primarily rely on their own data sources to get insight into pupil learning outcomes.

3.2. Social network data

3.2.1. Participants

Because of the intensive data collection (i.e. social network analysis combined with interviews), only six out of 10 schools out of the larger project could be asked to participate in this study to achieve high response rates. Heterogeneity was searched in the geographical location of the schools in Flanders. One of the schools did not achieve a sufficiently high response rate for the social network analysis (i.e. 80%) and was excluded from the analysis.

Social network data were collected in one teacher team in each of the schools. The teams teach fifth grade pupils in an academic track in economics and languages (16- to 17-year-olds) for one school year. These interdisciplinary teams are collectively responsible for the learning of the aforementioned pupil group. Two to three times a year, the teams are obliged to discuss the pupils' learning outcomes in a formal team meeting. During the school year, these meetings serve to discuss pupils' learning progress. In the last team meeting of the year, team members deliberate whether or not pupils will successfully complete their year.

Apart from team McKinley, in which 13 teachers are involved, the teams generally consist of 11 teachers (Table 1). In team Melrose, the response rate is 82%. The maximum response rate (100%) is reached in all other participating teams.

The participation of five teams in this study provides opportunities for in-depth investigation into the similarities and differences in structural interaction patterns within and across schools. The high response rates in each school imply that accurate conclusions can be drawn on the similarities and differences between networks across the data use phases. Across the schools, 576 data points ensure that some tendencies can be revealed on network changes across the data use phases. Additionally, sufficient variation is present to allow us to take a closer look at the diversity of network changes across the schools.

3.2.2. Instrument

Data were collected by means of an online survey. Next to general questions (e.g. gender, teaching course), two types of questions regarding teachers' data use interactions were included.

Table 1
Teams' response rates (social network analysis).

Team name	N	Response rate (%)
Riverbank	11	100
Northvale	11	100
Melrose	11	82
McKinley	13	100
Colby	11	100

The questionnaire distinguished between formal, obliged interactions (i.e. the team meetings to discuss and evaluate pupils' learning outcomes) and informal interactions. The scales on formal interactions were only used to distinguish formal from informal interactions. The analyses of this study only concerned the social network questions on informal interactions with regard to the use of pupil learning outcome data.

For each of the data use phases (i.e. discuss, interpret, diagnose, take action), a social network question was included in the questionnaire (e.g. 'Which of the following colleagues do you consult to discuss pupil learning outcome data?'). Subsequently, all members of the teacher team were listed.

3.2.3. Analyses

For each team, the density, reciprocity and centralization measures were calculated for the data use networks, using the UCINET 6.0 software package (Borgatti, Everett, & Freeman, 2002).

For all the network measures, the value can range between 0 and 1. For density, a value closer to 1 indicates higher cohesion in the network. Reciprocity close to 1 means a high amount of mutual ties, and higher centralization demonstrates the network importance of one or a few actors.

Data use involves phases of discussing, interpreting, diagnosing and taking action upon data. Thus, although data were collected cross-sectionally, the different networks cannot be seen as independent of each other. A first step to examine whether or not networks change across the data use phases was to calculate Quadric Assignment Procedure (QAP) correlations. This type of correlation, specifically designed for social network data, is a measure to evaluate the extent to which the same connections are formed in different networks with the same actors (Borgatti et al., 2002). Therefore, the measure provides an indication of the interrelatedness of different networks with the same actors, and can be used to measure overlap of the different networks in each team. Similar to other correlation coefficients, QAP correlations can range between 0 (no correlation) to 1 (perfect correlation), with values closer to 1 indicating a higher number of the same connections between the same actors across different networks.

In a next step, we obtained insights into how the networks differ across the phases of data use. Next to the interpretation of the density, reciprocity and centralization measures at network level, we provided insight into how individual teachers' networks change, since changes in individuals' networks are reflected at network level. Because of the interdependency of the data use phases and our conceptualization of data use as a cyclic process, we handled the data as longitudinal. This means that the discuss phase is approached as the start of data use, after which phases of interpretation, diagnosis and action complete the process. Although the data were gathered cross-sectionally, the data use phases can be seen as following each other. We specified a Stochastic Actor Oriented Model (SAOM) in Rsiena which provided insights into differences across the data use networks at teacher level (Ripley, Snijders, Boda, Vörös, & Preciado, 2016).

In the development of the SAOM, we first specified a theoretical model that could be tested in the different teams. General structural network characteristics (i.e. outdegree, reciprocity and transitive triplets) were included by evaluation effects following conventional model development in Rsiena (Snijders, Van de Bunt, & Steglich, 2010). The outdegree variable can be seen as a translation of density measures at actor level and provides insights into how teachers' interaction seeking behaviour changes across different phases of data use. Reciprocity is in this type of analysis also evaluated at actor level. Additionally to the general network characteristics, we added a popularity effect that reflects centralization at actor level. The evaluation effect of indegree popularity evaluates whether teachers generally consult more popular actors (e.g. expert colleagues) throughout the data use cycle.

The described SAOM was tested in all teams separately. Convergence of the effects in all models was sufficient (t-statistic < 0.1). In order to generalize the aforementioned model to some extent across the teams, a meta-analysis was conducted in Rsiena (Ripley et al., 2016). The meta-analysis was used to test the significance of parameters across the teams (Fisher test).

3.3. Qualitative data

Next to insights into structural interaction patterns, a purpose of the study was to generate knowledge about teachers' interactive learning activities. For this reason, qualitative data complement the social network data.

3.3.1. Participants

Out of the five teacher teams who participated in the social network questionnaire, 12 teachers were interviewed. Within each teacher team, three teachers were randomly asked to participate in the qualitative data collection process. Due to drop-out in teams Riverbank, Melrose and McKinley, a minimum of two teachers was interviewed within each team. Participation of all teachers was voluntary and not related to their network position, in order to achieve sufficient heterogeneity on teachers' interactive learning activities in the data set.

The 12 teachers varied in gender (six were male; six were female), teaching experience (five to 30 years) and teaching course (Dutch, English, French, German, history and chemistry). An overview of the main characteristics of all participating teachers is provided in Table 2.

3.3.2. Interviews and coding

We used semi-structured interviews to investigate the second research question. Participants' answers to the social network questions described earlier, formed the starting point of our interviews.

We provided the teachers with an overview of the colleagues they consulted. Then we asked them which learning activities occurred with these colleagues using an open question so that participants' answers were not restricted to the concepts we had set forward (e.g., 'What actually happens when you consult these colleagues on pupil learning outcomes? Can you recall real-life situations?). Subsequently, we posed additional questions on the Little (1990) framework (e.g., 'To whom amongst your colleagues do you ask advice on pupil learning outcomes? Can you sketch out such a situation?').

The interviews had an average duration of 45 min and were transcribed ad verbatim. Afterwards, the interviews were coded

Table 2
Characteristics of interview participants.

Team name	Participant	Gender	Teaching experience	Course(s)
Riverbank	Peter	Male	10–15	Dutch
	John	Male	10–15	German
Northvale	Kristen	Female	0–5	History
	Chandler	Male	10–15	Dutch
	Monica	Female	15–20	French
Melrose	Ross	Male	15–20	History
	Joey	Male	5–10	English
McKinley	Jennifer	Female	5–10	Dutch, English
	Frank	Male	15–20	Chemistry
Colby	Rachel	Female	10–15	English
	Phoebe	Female	15–20	Dutch
	Susan	Female	15–20	German

using Nvivo 10 software.

First, a researcher (further: researcher A) coded half of the interviews inductively by providing interview fragments with an open code (Pandit, 1996). Second, researcher A discussed the open codes with a second researcher (further: researcher B). Both researchers evaluated the validity of the open codes, which resulted in the need to concretize or rephrase certain codes. Subsequently, researcher A finished the open coding. Agreements were made between researchers A and B on the conceptual characteristics of axial codes (see Table 3).

Subsequently, the coding process took a deductive approach. Researchers A and B independently put open codes of seven randomly chosen interviews under the axial codes (step 4). The inter-rater reliability on the axial coding (headcodes) was calculated. A substantial Cohen's kappa of 0.74 was found (Sim & Wright, 2005). Finally, disagreements between the coding of both researchers were discussed to assure validity in the rest of the axial coding, which was finalized by researcher A.

3.3.3. Analyses

Whereas the social network data were analysed via a whole network approach, we used an ego network approach in the analysis of the interview data to deepen the results of the social network analyses. To extend and complement the actor-oriented approach of the social network analysis, we binarized the qualitative data on the level of headcodes for each participant. Score 1 was given to a participant if a headcode was present in the interview, score 0 if this was not the case. Binarization is a robust technique to obtain insight into the appearance of phenomena across or within participants (Onwuegbuzie, 2003). Since all conceptual topics were questioned in all semi-structured interviews, this technique was suitable for the present dataset. The advantage of binarizing relative to counting citations is that it purges the personal differences of participants (e.g. talkative versus introverted participants).

We conducted cross-case analysis of the network activities of the 12 participants. We started from the binarization of headcodes. Furthermore, we searched for similarities and differences in the interviews to provide a rich description of participants' interactive learning activities following the principles of framework analysis (Maso & Smaling, 1998).

4. Results

4.1. Structural interaction patterns

In order to answer the research question on similarities and changes in structural interaction patterns in teacher teams, we investigate the density, reciprocity and centralization measures across the network in each team (Table 4).

Table 4
Descriptive statistics for network composition.

Statistic	Team	Discuss	Interpret	Diagnose	Action
Average Degree	Riverbank	4.46	3.73	4.09	3.27
	Northvale	3.09	2.64	1.82	1.09
	Melrose	2.00	2.09	1.55	1.18
	McKinley	3.38	2.56	2.06	2
	Colby	3.64	4.00	2.00	1.82
Density	Riverbank	0.45	0.37	0.41	0.33
	Northvale	0.31	0.26	0.18	0.11
	Melrose	0.20	0.21	0.16	0.12
	McKinley	0.23	0.17	0.14	0.13
	Colby	0.36	0.40	0.20	0.18
Reciprocity	Riverbank	0.58	0.64	0.45	0.44
	Northvale	0.21	0.16	0.05	0.20
	Melrose	0.29	0.35	0.21	0.30
	McKinley	0.54	0.64	0.32	0.33
	Colby	0.43	0.38	0.29	0.33
Centralization	Riverbank	0.43	0.52	0.48	0.58
	Northvale	0.84	0.90	1	0.60
	Melrose	0.49	0.48	0.30	0.34
	McKinley	0.66	0.26	0.38	0.38
	Colby	0.41	0.73	0.37	0.39

The average degree in social network analysis reflects the average number of links per teacher. In other words, to how many colleagues teachers head for the use of pupil learning outcome data. Looking at the average degree of teams, we find fluctuations across the data use phases. For example, in team Riverbank, on average 4 to 5 colleagues are consulted to discuss pupil learning outcome data. However, when it comes to the interpretation of data, the diagnosis of problems or taking action, teachers consult less colleagues. In three out of five teams (i.e. Northvale, Melrose, McKinley) the tendency is that the average degree decreases across the data use phases. This means that, on average, teachers in these teams will systematically consult less colleagues from the discussion towards the action phase. For teams Riverbank and Colby, the tendency of degree fluctuation is less clear.

The fluctuation of average degree is reflected in the density statistics. Density is the ratio of the number of interactions and the number of possible interactions in the team. For example, a network in which 10 interactions are possible and 8 interactions are present will have a density measure of 0.80, which indicates that 80% of the possible interactions are used. Overall, the density statistics are low in all the networks of all schools. In team Riverbank, a 0.40 value for density is reached in the discuss and diagnose phase of data use, and in team Colby, the same value is reached in the interpretation network. This means that in these teams and during these phases, 40% of the possible ties are used. However, generally, lower density degrees are measured, ranging from 0.11 (team Northvale – action network) to 0.37 (team Riverbank –

Table 3
Coding scheme.

	Axial Code	Conceptual characteristics
Learning activities (Little, 1990)	Storytelling	- Asking/talking about learning outcomes - Individually driven: gathering information for own practice - Quasi no interdependency
	Helping	- Advice related to learning outcomes - Individually driven: derives from a need/question - Little interdependency: need of the advice-seeker
	Sharing	- Distribution of materials, strategies, information - Driven from a collective perspective: serving the teacher team - Little interdependency: individual responsibility of teachers
	Joint work	- Actively working together (making arrangements, etc.) - Driven from a collective perspective: make the teacher team work more efficient/better - High interdependency: joint work is reflected in individual practice

interpretation). This implies that 11%–37% from all possible network ties are accomplished.

Reciprocity is the ratio of the number of mutual interactions (i.e. if teacher A turns to B for data interpretation, teacher B also turns to A). For example, a network in which 10 interactions are present and 7 of them are mutual, a reciprocity value of 0.70 is calculated, which indicates that 70% of the interactions are mutual. Reciprocity values show that a moderate number of interactions is reciprocated in teams Riverbank, McKinley and Colby and a small number is reciprocated in teams Northvale and Melrose. In teams Riverbank, McKinley and Colby, reciprocity values of 0.29 (team Colby – Diagnose network) to 0.64 (team Riverbank – Interpret network) indicate that 29%–64% of the ties that exist are mutual ties. In teams Northvale and Melrose, the reciprocity measures are lower, ranging from 0.05 (team Northvale – Diagnose network) to 0.35 (team Melrose – Interpret network). In these teams, 5%–35% of the ties that teachers send are reciprocated. Within teams, the reciprocity measures fluctuate, which implies that the level of reciprocity depends on the data use phase.

Centralization reflects the extent to which teachers in networks all turn one or a few colleagues. For example, if all interactions in a team are directed to one teacher (e.g. an expert in data use), the centralization value will be 1 (i.e. 100% of the interactions are directed to one teacher). In terms of centralization, Table 4 shows that team Northvale is highly centralized. The centrality measures of 0.60–1 in this team indicate that 60%–100% of the data use relations in the team are directed at one or a few central actors. Centralization values of 0.26 (team McKinley – Interpret network) to 0.73 (team Colby – Interpret network) indicate that centralization is moderately to quite high in all other teams. This means that few actors are more important than others in the data use networks (e.g. data use experts as brokers). Centralization measures fluctuate in all teams, which means that in some data use phases, the popular actors are more important than in others.

The descriptive statistics show fluctuations of all measures (i.e. density, reciprocity and centralization) across the data use phases. However, they do not provide evidence on whether or not differences between the networks are significant. To do so, a first step is to take a closer look at the QAP correlations of the discuss, interpret, diagnose and action networks (Table 5). These correlations reflect the extent to which connections between teachers are identical across the networks. Overall, we find quite high correlations between the networks (all significant at $p < 0.01$ level). In team Melrose, the discuss and action networks correlate rather weakly, indicated by a correlation coefficient of 0.45. However, all other correlations in all teams exceed the 0.50 value, and in most cases the 0.70 value, whereby the different data use networks can be interpreted as moderately to strongly correlating. This means that there are high similarities in the connections between teachers across the data use phases.

At the same time, we find that in none of the teams are the different data use networks identical across phases, which explains the differences in density, reciprocity and centralization. Although the discuss and interpret networks in team Melrose and the diagnose and action networks in team McKinley approximate a perfect correlation with coefficients of 0.92 and 0.98 respectively, these are exceptions. Generally, we determine at least a small number of differences in structural interaction patterns within the teacher teams across the data use phases. This can both mean that teachers consult a lower or higher number of colleagues, and the same or different colleagues across the data use phases.

Table 5
Network correlations between data use phases.

	Riverbank	Northvale	Melrose	McKinley	Colby
Discuss – interpret	0.78 **	0.85 **	0.92 **	0.82 **	0.85 **
Discuss – Diagnose	0.85 **	0.70 **	0.60 **	0.68 **	0.61 **
Discuss – Action	0.70 **	0.52 **	0.45 **	0.66 **	0.62 **
Interpret – Diagnose	0.70 **	0.79 **	0.71 **	0.80 **	0.57 **
Interpret – Action	0.82 **	0.58 **	0.57 **	0.81 **	0.58 **
Diagnose - Action	0.84 **	0.67 **	0.78 **	0.98 **	0.83 **

**$p < 0.01$.

The differences in structural interaction patterns across the data use phases were further explored at actor level within the five teacher teams. Table 6 presents the results of the Stochastic Actor Oriented Model (SAOM) that was tested in the five teams.

The rate parameters reflect the average number of changes per actor between two data use phases. For example, in team Riverbank, the rate parameter of 1.68 (P1) indicates that teachers in this team have on average 1.68 opportunities to change their ties from the discuss to the interpret phase. This does not mean however that all teachers use all these change opportunities and, for example, drop or establish new connections. The rate parameters suggest that the number of connection changes peaks from interpretation to diagnosing data in teams Riverbank, Melrose and Colby, from diagnosing to action in team Northvale, and from discussion to interpretation in team McKinley.

The structural and popularity effects provide insights into the changes at actor level that do occur across the data use phases. The outdegree of teachers reflects how many colleagues teachers consult in a network. Therefore, the negative outdegree effects in all teams indicate decreasing tie probabilities across the data use phases. In other words, teachers engage in less interactions for action compared to discussion, interpretation and diagnosis. The meta-analysis confirms that there is a tendency for a decrease in outdegree in all teams. This means that, on average, teachers are likely to drop ties across the data use phases. This was also reflected in the fading outdegree values at team level in most teams (Table 6).

In contrast, teachers are more likely to engage in reciprocated ties across the data use phases. Teacher interactions are more often mutual in their action networks, compared to their discussion, interpretation and diagnosing networks. Although this effect is only significant in team Melrose, the meta-analysis confirms that it is unlikely that reciprocity remains stable or decreases across the data use phases. Thus, the teachers in our participating teacher teams (and particularly in team Melrose) prefer closer relations in the transition from the discuss to the action phase.

Because centralization can only be calculated at network level, indegree popularity was included in the model to approximate this measure at the individual level (cf. method section). This effect reflects whether teachers turn to more popular actors throughout data use. Mixed results are found for the indegree popularity effect. In team Riverbank, teachers show the tendency to engage less in interactions with more popular actors throughout the data use process. In teams Melrose and Colby, the opposite evolution is found. In these teams, teachers tend to search for interaction with more popular actors in the context of data use. Therefore, no clear overall tendency of indegree popularity can be concluded from the meta-analysis.

The social network analyses at team level indicate that changes occur in structural interaction patterns across the data use cycle. Although teams strongly differ in the extent to which the role of central actors changes across the phases (i.e. indegree-popularity), similarities are found in the likeliness to engage in (mutual) connections with colleagues (i.e. density/outdegree and reciprocity). The general tendency is that teachers will engage in a smaller number of ties but are interested in more reciprocated ties throughout the different data use phases.

Table 6
Results for the stochastic Actor oriented model (SAOM).

	Rate parameters	Structural effects		Popularity effects
	Estimate (s.e.)	Outdegree (s.e.)	Reciprocity (s.e.)	Indegree popularity (s.e.)
Riverbank	P1: 1.68 (0.53) P2: 2.77 (0.93) P3: 1.33 (0.43)	−1.18 (0.60) *	0.56 (0.49)	−0.32 (0.17)*
Northvale	P1: 0.91 (0.34) P2: 1.52 (0.52) P3: 2.90 (1.03)	−3.97 (1.74) *	0.23 (1.18)	0.05 (0.46)
Melrose	P1: 0.39 (0.22) P2: 1.62 (0.57) P3: 0.98 (0.43)	−3.55 (1.36)**	1.66 (0.87)*	0.18 (0.35)*
McKinley	P1: 1.83 (0.53) P2: 1.42 (0.45) P3: 0.13 (0.13)	−3.74 (1.61)**	1.75 (1.18)	0.17 (0.32)
Colby	P1: 0.89 (0.33) P2: 4.00 (1.11) P3: 0.78 (0.34)	−3.62 (0.91)**	0.35 (0.64)	0.26 (0.13)*
Fisher test (meta): L-S χ^2 - R-S χ^2		56.72** - 0.11	2.25–20.85*	9.43–13.79

*$p < 0.05$.
**$p < 0.01$.
P1: discuss – interpret.
P2: interpret – diagnose.
P3: diagnose – action.

4.2. Teachers' interactive learning activities

The structural interaction patterns indicate that data use networks are rather sparse. This provides teachers with few opportunities for interactive learning activities. Also, teachers tend to reciprocate more ties in later phases in the data use cycle, which increases the depth of relationships. In this section, the qualitative data are used to complement these findings by looking into the degree of interdependency in interactive learning activities that teachers report within their personal (ego) networks in the context of data use.

Depending on the degree of interdependency, we distinguish between co-operative activities (i.e. storytelling, helping and sharing) and collaborative activities (i.e. joint work) to describe teachers' interactive learning activities. Table 7 provides an overview of the binarized results for the network activities that teachers mentioned in all interviews.

We find that, overall, the greatest share of teachers report learning activities with regard to their discussion network, while the smallest share report them with regard to their diagnosing network. Generally, the number of teachers reporting learning activities in their discuss and interpretation networks is higher than teachers providing evidence of learning activities in diagnosing and action networks.

Discussing pupil learning outcome data is often triggered by individual teachers. Most of the time, discussions on pupil learning outcome data are initiated due to poor performances in class tests. In a lot of cases, the other data use phases (interpretation, diagnosis and action) are undertaken individually by the teachers, but teachers feel frustrated about the effort they have put into teaching the subject and feel the need to discuss pupil learning outcome data with colleagues. In the case of interpreting pupil learning outcome data, teachers aim to share their pupil outcomes with colleagues, and add context to it. A common example is that teachers want to discuss pupil learning outcome data with colleagues in order to know how the pupil is doing in other courses. This contextualisation can lead to teachers reframing their first interpretation about the (poor) learning outcomes. In some cases, the contextualisation teachers are looking for results in a common diagnosis of problems on the basis of pupil learning outcome data. For example, teachers may ask colleagues whether or not test questions were too difficult for the pupil group. In addition, the action phase of data use can result from this type of situation. Some participants indicate that these (informal) discussions may result in sharing strategies or making agreements to cope with problematic behaviour or poor learning results.

Looking at the level of interdependency, the results show that most network activities on the part of teachers are at the lowest level of interdependency (i.e. storytelling). All interviewed teachers report at least one example of storytelling with (some of) their colleagues in the teacher team. Storytelling appears to be a common learning activity. Given its low level of interdependency, storytelling can occur ad hoc. For example, when a teacher starts a storytelling conversation because he or she has just noticed that a pupil is under-achieving in his or her course. Storytelling activities are mainly reported by teachers in their discuss and interpret networks.

When the level of interdependency increases, fewer teachers report this type of network activity and the learning activities are situated in later phases in the data use cycle. For example, helping is only reported by one teacher in the discuss and diagnosis phase and by four teachers in the action phase. This means that, of the

Table 7
Teachers' network activities (N = 12).

		Discuss	Interpret	Diagnose	Action
Co-operation	Storytelling	11	9	3	0
	Helping	1	0	1	4
	Sharing	0	0	0	2
Collaboration	Joint work	0	0	0	1

interviewed teachers, the greatest number asks or provides help or advice for action on the basis of pupil learning outcome data. The most common examples of helping activities related to the action phase are related to improving assessment practices. For example, (often language) teachers struggle with marking specific exercises on tests and ask colleagues for advice on how to better align their marking across pupils and tests. Sharing and joint work activities are almost absent in the interviewed teachers' data use networks. Whereas two teachers report sharing activities in their action network, only one teacher (Peter) indicates engaging in joint work for action upon pupil learning outcome data. The few examples of sharing practices involve, for example, sharing strategies to introduce peer assessment or to assess a particular student with learning disorders. The joint work example refers to making arrangements on curriculum subjects that are (not) evaluated.

4.3. Illustration: the case of John in team Riverbank

The social network analysis and the qualitative analysis are complementary in terms of the finding that data use cannot be considered a linear process, not in terms of structural interaction patterns, nor in terms of interactive learning activities that occur in teachers' personal networks. The core findings are that teachers' networks change by engaging in fewer but more intense connections with colleagues in later phases of the data use cycle. Only in the action phase do learning activities with higher levels of interdependency than storytelling occur. The case of John of team Riverbank is illustrative for these findings.

John's personal networks do not change profoundly across the data use phases, but his diagnosis and action network are slightly smaller than his discuss and interpret networks. Whereas he reports connections with five out of 10 colleagues for discussion and interpretation of pupil learning outcome data (i.e. Lydia, Alex, Gloria, Kelly and Kevin), the connection with Alex is dropped when it comes to diagnosis and action. John indicates that the discussion and interpretation of pupil learning outcome data generally takes place in daily conversations among teachers (i.e. storytelling), for example about pupils' lacking motivation or having a poor attitude with regard to his course (i.e. German language). These storytelling activities also serve John's interpretation of (certain) pupil learning outcome data. For example, when pupils' test scores are low, John often asks his colleagues in foreign languages whether or not they notice the same in their courses. According to John, this helps him to interpret whether the problem is specifically related to the German language course.

"In the beginning of the school year, the results of my pupils were very disappointing. Remarkable compared to other years. And then I consulted my colleagues in English language and French language, because these are also foreign languages. They hadn't noticed similar things yet because they were still rehearsing the curriculum of the previous years. But for German language, there was not much to rehearse [laughs].

So I thought: 'Then it might be the transition to the fifth grade curriculum that is difficult for my pupils'. And my pupils confirmed this. So I slowed down the tempo of the lessons and proposed remedial work during lunch break so that my pupils would be able to catch up as much as possible."

In John's diagnosing and action networks, the level of interdependency in his interactive learning activities is higher. John asks help or advice in both networks, for example when he does not have a clue as to why test results for a certain pupil group remain low (i.e. diagnosis) or in (re)designing workable writing assignments for tests or exams (i.e. action). In his action network, John also aims to share strategies and materials. For example, he asks colleagues to share speaking assignments in order to create a better alignment in speaking assignments across the language teachers. Although John is one of the most interactive teachers in the present data set, he indicates that he almost never engages in joint work activities with colleagues in his data use networks.

"Are there any colleagues in your network with whom you work together to talk about your pupils' learning outcomes and to investigate how these learning outcomes can improve?

That is not really working together, but more informal, in the staff room. Those are occasions when you meet each other and you can exchange information. But consciously working together… not so much. Actually, …almost never."

5. Discussion and conclusion

Although teacher interactions in the context of data use are highly valued, little is known about similarities and changes in teacher interactions in the data use cycle of discussion, interpretation, diagnosis and action. The combination of social network analysis and qualitative data in this study provided insights into (1) similarities and differences in structural interaction patterns in five Flemish teacher teams across data use phases, and (2) interactive learning activities that are embedded in 12 teachers' personal data use networks within the five teams.

The analysis of both research questions revealed that teachers' networks change across the data use phases, both in terms of structural interaction patterns and in terms of interactive learning activities. Generally speaking, the tendency is that teachers engage in fewer but more intense interactions with colleagues when progressing through the phases. The social network analysis showed that teachers are likely to drop connections with colleagues and invest more in mutual interactions. The qualitative analysis indicated that teacher interactions also become more intense in terms of interactive learning activities. Participants' interactions with regard to discussion and interpretation involve learning activities of lower levels of interdependency (i.e. storytelling). Higher levels of interdependency (i.e. helping, sharing, joint work) are reached in teachers' action networks.

Finding limited (mutual) interactions in teacher teams is similar to the results of the few network studies we found in the context of data use (Hubers et al., 2016; Farley-Ripple & Buttram, 2014; Keuning et al., 2016). Also, low levels of interdependency in the participating teacher teams is not uncommon, and particularly not given the Flemish (data use) research context (Katz & Earl, 2010; Kwakman, 2003; Little, 1990; OECD, 2013; Van Gasse et al., 2016; Van Waes et al., 2016). In Flanders, data use is often carried out individually by teachers and Flemish teachers in general do not intensively engage in activities that demand high degrees of interdependency with their colleagues (OECD, 2013; Van Gasse et al., 2016; Van Waes et al., 2016).

The novelty of findings can be found in the granularity in which changes in teacher interactions are revealed. The combination of research methods provided opportunities to expose with significant detail how teacher interactions change across the data use cycle. Previous research already showed that data analysing and interpretation skills are needed in the discussion and interpretation phase and advanced pedagogical content knowledge for correct problem diagnosis and the design of appropriate instructional change (Gummer & Mandinach, 2015; Marsh & Farrell, 2015). This study reveals that the 'shift' in the type of knowledge and skills

needed for data use diagnosis and action is accompanied by changes in teacher interactions. Whereas some (more) colleagues may be consulted for the discussion and interpretation of pupil learning outcome data, fewer teachers are preferred to carry out the diagnosis and action phase with. Additionally, the interactions of teachers in the action phase are characterized by activities of higher interdependency (i.e. helping, sharing, joint work).

For the participating teachers in this study, fewer colleagues seem convenient to interact with for concrete and course specific problem solving or improvement (i.e. data use action) than for discussion and interpretation of data. At the same time, when the number of teacher interactions decreases, the teachers invest in interactions of higher interdependency. A possible explanation can lie in the advanced pedagogical knowledge required for data use action (Gummer & Mandinach). Although the five teacher teams share the responsibility for the learning of one specific pupil group, the teams are composed interdisciplinary. The qualitative data, including the case of John, indicate the likeliness that teachers search for colleagues teaching related courses when it comes to course-specific problem solving. A footnote in this regard is, however, that there must be additional explanations for whom is consulted in data use. The case of John, for example, shows that not all colleagues in his action network are language teachers. Thus, although the knowledge and skills associated with data use action can explain the smaller and more intense networks of the participating teachers to some extent, future research can invest in examining alternative explanations.

Unravelling teachers' interactions by the combination of social network data and teachers 'stories' behind their personal networks contribute to the current literature base both theoretically and methodologically. Not only does this study confirm that teacher interactions change across the data use phases, in-depth insights are provided into how networks change in terms of structure and activities. Nevertheless, some limitations remain. First of all, there are limitations with regard to the methodological approach. For example, we investigated teacher interactions within specific team boundaries. This implies that interactions of participating teachers with colleagues outside these boundaries were not included. Additionally, the combination of social network analysis and qualitative analysis required an intensive data collection. Therefore, our sample of 5 teams is small, whereby the current findings cannot be generalized. Future research can address both methodological issues, for example by using an ego network approach without strict team boundaries and by investing in a greater sample size. Another limitation is situated at theoretical level. Up to now, it remains unclear how effective networks look like in the context of data use. The network literature generally defines effective networks in terms of high density and reciprocity and low centralization (Moolenaar, 2012). However, it is doubtful whether this can be directly translated to data use networks, given that the complexity of data use may lead to consultation with a few (expert) colleagues to contribute to individual data use rather than engaging in interactions with all team members (Cosner, 2011; Datnow & Hubbard, 2016). Additionally, discussion is still ongoing with regard to the contribution of learning activities with low levels of interdependency (i.e. storytelling or helping) to teachers' professional development and classroom practice. Whereas some studies support the value of these activities (Van Gasse et al., 2016; Van Waes et al., 2016), others are more sceptical about their impact on teacher learning (Katz & Earl, 2010; Meirink, Meijer, Verloop, & Bergen, 2009; Van Gasse et al., 2016; Van Waes et al., 2016). Therefore, future research should aim to provide insight into which network constellations and interactive learning activities result in thorough data discussion, interpretation, diagnosis and action.

The kinds of activities in the different data use phases affect how teachers use their networks. This has implications for both research and practice. To start with, teacher collaboration needs to be approached with sufficient granularity. The current study shows that interactions among teachers are very different depending on where they are situated in the data use cycle. For practitioners, awareness is needed that instructional improvement based on data requires higher levels of interdependency. After all, this study shows no storytelling in teachers' small action networks. Therefore, for instructional improvement, the aim does not have to be the involvement of all teachers. More important is setting common goals to encourage teachers' engagement in activities of higher interdependency with (some) colleagues (Levin & Datnow, 2012). For the great number of intervention studies in the field of data use, the results imply that intervention designs need to be well-considered with regard to teacher interactions. Acknowledging that teachers use their network differently and engage in different learning activities across the data use phases can support the outcomes and the sustainability of interventions. Researchers need to think about whether it is more useful to implement rather artificial compositions of teams or to embed interventions in existing social structures. And, in addition, to which extent the purpose should be that all teachers are equally involved and interact with high interdependency across the data cycle. To this end, future research on network constellations, interactive learning activities and their effects on instructional change is essential. Altogether, keeping in mind teachers' natural tendency of interacting throughout the data use cycle can take both research and practice a step further.

Teacher interactions have been valued for some time in the context of data use. This study was a useful first step in exploring how teacher interactions change across different data use phases. The combination of social network analysis with qualitative analysis exposed teacher interactions with great detail. Therefore, the study shed new light on teacher interactions with the theoretical and methodological granularity needed to do justice to the complexity of teachers' daily practice.

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