The transformation of schools' social networks during a data-based decision making reform

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The Transformation of Schools' Social Networks During a Data-Based Decision Making Reform

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Context: *Collaboration within school teams is considered to be important to build the capacity school teams need to work in a data-based way. In a school characterized by a strong collaborative culture, teachers may have more access to the knowledge and skills for analyzing data, teachers have more opportunity to discuss the performance goals to be set, and they also can share effective teaching strategies to achieve those goals. Although many studies on data-based decision making (DBDM) foreground the importance of teacher collaboration, our knowledge of what such collaboration looks like and how such collaboration may change during a DBDM reform remains limited.*

Objective: *The current study uses a social network perspective to explore how collaboration in 32 elementary schools in the Netherlands takes shape in the interactions among teachers as they engage in a DBDM reform project.*

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Research Design: *Schools' social networks were examined at the start of the intervention and after having participated 1 year in the DBDM reform. Social networks regarding three DBDM topics are examined: (1) discussing student achievement; (2) discussing achievement goals; (3) and discussing instructional strategies. The density, reciprocity, and centralization of these networks were calculated, and multivariate multiple regression analysis was used to analyze changes over time.*

Conclusion: *Findings suggest that teachers' DBDM related networks transform during the intervention, especially regarding the discussion of student achievement data: although the number of relationships remains stable, more reciprocal relationships are formed, and this network becomes less centralized around one or a few influential staff members.*

INTRODUCTION

Around the world, there is growing emphasis on data use in education (Mandinach & Gummer, 2015). In the international literature, the use of data to improve teaching and learning is frequently referred to as data-based decision making (DBDM). Ikemoto and Marsh (2007) referred to DBDM as "teachers, principals, and administrators systematically collecting and analyzing data to guide a range of decisions to help improve the success of students and schools" (p. 108). Teachers' use of student achievement data to evaluate student progress, to provide tailor-made instruction, and to develop strategies for maximizing performance is considered to have a positive influence on student outcomes (Schildkamp, Ehren, & Lai, 2012).

An important factor to support DBDM is a collaborative school culture (Ingram, Louis, & Schroeder, 2004; Schildkamp & Lai, 2013b; Schildkamp & Poortman, 2015). In a school characterized by a strong collaborative culture, teachers may have access to the knowledge and skills for analyzing data, have the opportunity to discuss challenging performance goals, and share effective teaching strategies to achieve those goals (Ingram et al., 2004; Lai & McNaughton, 2009; Schildkamp & Lai, 2013a). Strong collaboration thus can be considered a precondition for DBDM, and therefore reform initiatives aimed at improving DBDM should encourage collaboration. Although studies on DBDM foreground the importance of teacher collaboration, our knowledge of what an optimal collaboration structure for DBDM looks like, and whether DBDM professional development can support such collaboration, is very limited. Therefore, the current study took a social network perspective to explore how collaboration takes shape in the interactions among teachers as they engage in a DBDM reform project. The change of the social networks at 32 elementary schools in the Netherlands was examined as they participated in a 2-year DBDM professional development reform.

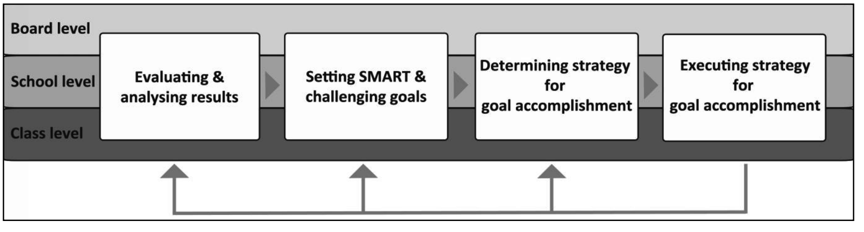
THEORETICAL FRAMEWORK

In the following section, first DBDM is defined and it is explained why collaboration is considered important for the successful implementation of a school reform like DBDM. Second, we explain how the social network perspective might help us understand collaboration patterns within schools, and we elaborate on what already is known about social network transformation during a reform initiative. Third, a brief description of the DBDM intervention studied in this paper is given. Finally, the hypotheses will be stated.

DATA-BASED DECISION MAKING AND THE IMPORTANCE OF COLLABORATION

Systematically analyzing student performance data, setting goals based on such data, and trying to accomplish maximum achievement for all students in the school is referred to as data-based decision making. In the context of this study, DBDM was broken down into four components at three levels, graphically represented in Figure 1, based on Visscher and Ehren (2011).

Figure 1. The components of DBDM at three levels



At the class, school, and board levels, student and school performance data is intended to be first *analyzed*, and decisions are intended to be made based on such data. The term "data" is relatively broad and can include several types of data to base decisions on (Schildkamp & Poortman, 2015). In this study, the primary focus was on standardized test results comparable to what is called *interim benchmark assessments* by Datnow and Hubbard (2015). In the Dutch context, a student monitoring system has been developed by the Central Institute of Test Development (Kamphuis & Moelands, 2000). This system includes a coherent set of tests for the longitudinal assessment of students' achievement throughout all grades of primary education. These tests, which are usually taken twice a year (in January and July), are available for all core subjects (mathematics, reading, spelling, vocabulary). The test results are converted into an ability scale for each subject, so student progress can be monitored over grades and school years (Kamphuis & Moelands, 2000). Furthermore, the accompanying student monitoring software enables teachers to monitor their students' strengths and weaknesses on the basis of these assessment results and to adapt their instruction accordingly.

The analysis of the assessment results is the starting point, but additional information, such as curriculum-based tests, classwork, homework, and classroom observations, also needs to be included because no single assessment provides all information to make informed decisions (Hamilton et al., 2009).

In the DBDM literature, the term 'decisions' implies a variety of actions that can be undertaken based on all such data, such as setting goals, adapting instruction, adapting the curriculum, evaluating the effectiveness of programs and practices, and reallocating time and resources as necessary (Earl & Katz, 2006; Hamilton et al., 2009; Ikemoto & Marsh, 2007; Mandinach, Gummer, & Muller, 2011). In Figure 1, the category *decisions* is broken down into *setting goals* based on the available data and *determining the strategies* that are intended to achieve those goals.

The chosen goals and strategies for goal accomplishment vary according to the level of decision making. At the group level, teachers may use student performance data to set goals in terms of desired achievement gain or skill attainment. To accomplish those goals, they may decide to use a specific instructional strategy or form an ability group to work on a specific topic (Dunn, Airola, Lo, & Garrison, 2013). At the school and school board levels, data can be used to highlight specific areas for improvement in the school(s). The strategies chosen often comprise policy decisions, for example regarding the allocation of resources, the adoption of instructional strategies throughout the entire school, or the modification of the curriculum.

The final step in Figure 1 is to *implement and execute the chosen strategies.* As Bennett (2011) and Anderson, Leithwood, and Strauss (2010) argued, the effects of the implementation activities are closely related to the quality of the inferences based on the data, the chosen approach to address the identified problems, and the expertise of school staff. If teachers, for example, draw invalid conclusions about students' learning needs, they are likely to implement a strategy that may not lead to the desired outcomes. Such invalid conclusions may be caused by a lack of knowledge of what the data say, but also by the quality of the test (Cronbach & Meehl, 1955) used for measuring student achievement. The quality of the test is among other things influenced by the extent to which the items in that test, as a sample of items from the universe of possible items, represent that universe well and as such provide a valid picture of how well a student masters specific subject matter content (Cronbach & Meehl, 1955).

Teachers' use of student achievement data for evaluating student progress, for providing tailor-made instruction, and for developing strategies for maximizing performance is considered to have a positive influence on student outcomes. However, the effectiveness of DBDM will strongly depend on the extent to which teachers possess or develop the required professional knowledge and skills for analyzing and interpreting the performance feedback, and for translating performance data into improvement strategies (Schildkamp & Poortman, 2015). Collaboration within school teams is important to build the capacity school teams need to work in a data-based way (Farley-Ripple & Buttram, 2015; Marsh, Bertrand, & Huguet, 2015). In a highly collaborative team, teachers might have more access to the knowledge and skills for analyzing data, have the opportunity to discuss challenging goals, and share effective teaching strategies to reach these goals (Farley-Ripple & Buttram, 2015; Jimerson & Wayman, 2015). A collaborative school culture is assumed to have a positive effect on the implementation of educational reforms such as DBDM (Ingram et al., 2004; Lai & McNaughton, 2009; Love, Stiles, Mundry, & DiRanna, 2008; Schildkamp & Lai, 2013a). Schools with strong collaboration patterns seem to facilitate the transfer of complex information and show improved individual and organizational performance. These schools are more characterized by the trust necessary for risk taking during reform. Teachers working in collaborative teams also seem to be more likely to improve their instructional practices and to have more access to expertise and support (Daly, Moolenaar, Bolivar, & Burke, 2010; Penuel, Sun, Frank, & Gallagher, 2012). Additionally, in schools characterized by strong relationships, the innovative climate is stronger (Moolenaar et al., 2014; Moolenaar, Daly, & Sleegers, 2010), indicating that there is a higher "collective willingness to adopt an open orientation toward new practices and change, and to collectively support and develop new knowledge, practices and refinements to meet organizational goals" (Moolenaar et al., 2014, p. 102).

More specifically, in their study of DBDM in high schools, Ingram et al. (2004) concluded that "teachers are more likely to mention systematic data collection and use when they are involved in groups looking at school processes" (p. 1280). Schildkamp and Lai (2013) stated that collaboration is essential for sustainable school improvement: collaboration reduces the isolation of the teaching profession and improves individual teachers' personal growth.

SOCIAL NETWORK CHARACTERISTICS FOR SCHOOL REFORM

What is the 'Optimal' DBDM social Network?

Both in the educational literature (Daly et al., 2010; Finnigan & Daly, 2012; Frank, Penuel, & Krause, 2015; Sun, Penuel, Frank, Gallagher, & Youngs, 2013) and in the literature on organization and management (Borgatti & Foster, 2003; Devine, Clayton, Philips, Dunford, & Melner, 1999; Sparrowe, Liden, Wayne, & Kraimer, 2001; Tsai, 2001), social networks are associated with team learning and organizational learning and performance. The success of the implementation of an innovation, such as DBDM, depends critically on the ability of the organization to internally distribute the knowledge, support, and resources necessary to promote practices related to this innovation (Frank et al., 2015).

Although studies on DBDM stressed the importance of teacher collaboration, our knowledge of what such collaboration looks like is still limited**.** The social network perspective might give us more insight into collaboration patterns that enhance the implementation of DBDM in schools (Daly, 2012).

Social network analysis is a systematic approach used to quantify and visualize the patterns of relationships (called 'ties') between actors (e.g. teachers) in a social network (e.g., a school) (Moolenaar, 2010). In this study we focused on three network measures that are generally used to define schools' network structure: density, centralization, and reciprocity (Moolenaar, 2012). *Density* refers to the concentration of relationships in a social network and is calculated as the total number of relationships in the network divided by the total number of possible relationships (Moolenaar, 2012). Since ties are considered paths through which information and knowledge can flow, it is assumed that the more relationships exist, the more access actors have to information and knowledge within the network (Borgatti & Ofem, 2010). Accordingly, in dense networks—with many ties—resources are moved more quickly than in networks with fewer ties (Scott, 2013). Dense networks are important for an innovative climate. Moolenaar, Daly, and Sleegers (2011) found that the more densely connected teachers were in regard to work-related and personal advice, the more they perceived their school's climate to be supportive of innovation. Moreover, Daly et al. (2010) found that school team members in a dense network during an educational reform project reported being able to enact the reform at a greater depth compared to those team members who were sparsely connected to each other. Furthermore, denser networks were associated with greater focus on teaching and learning as well as increased collective action, efficacy, and collective satisfaction. Finnigan and

Daly (2011) pointed to the fact that more dense networks provide a better basis for meeting collective goals, and the stable relationships within them enable cooperation, innovation, and the exchange of knowledge. Daly and Finnigan (2011) however stressed that stable ties in dense networks may form a barrier for the assimilation of new external information just as for flexible organizational responses to external stimuli.

A second measurement of the compactness of a network complementary to density is the centralization of the network (Scott, 2013). C*entralization* indicates the degree to which a network is centralized around one or more "popular" actors (Moolenaar, 2012). The degree of centralization that is effective is strongly dependent on the goal of the network. More centralized networks are positively related with the exchange of simple information, technical knowledge and routines (Cummings & Cross, 2003) while decentralized structures are more suited for solving complex group tasks (Sparrowe et al., 2001) and are more flexible toward change and innovation (Daly & Finnigan, 2011).

Finally, the extent to which relationships in a network are reciprocal is indicated by its *reciprocity* (Moolenaar, 2012), which reflects the number of reciprocal relationships within a network divided by the total sum of all relationships in the network (whether reciprocal or not). Kilduff and Tsai (2003) suggested that sharing complex information and knowledge is correlated with the existing number of reciprocal relationships.

Based on the literature, we assumed that social networks that support DBDM are characterized by many ties through which information can flow (high density), equal relationships across the network to ensure that teachers collectively participate in the DBDM process (low centralization), and a high number of reciprocal ties through which complex information and knowledge about DBDM is exchanged. These types of networks were assumed to support the exchange of complex information, such as knowledge about analyzing and interpreting data or effective teaching strategies.

What does DBDM collaboration look like in practice?

Farley-Ripple and Buttram (2015) performed a case study on the structure of data advice networks compared to teachers' regular professional network. Findings showed that teachers' data-use networks were highly similar to their "regular professional network" in terms of which individual teachers seek support from whom, but different in terms of density and centralization: professional networks were denser than the data advice network, whereas the latter was more centralized. However, as Farley-Ripple and Buttram emphasized, this case study was done in a high-performing elementary school, a prime example of a school who already worked in a DBDM way; thus the findings might not be generalizable to other schools.

In their study on schools' social networks Atteberry and Bryk (2010) found that in many schools teachers work in isolation, experience little task interdependence, and have few opportunities for professional collaboration. Teachers mainly discuss work-related issues with teachers within the same grade level, also known as the "homophily" principle (*"the principle that a contact between similar people occurs at a higher rate than between dissimilar people"),* or with the teachers in the classroom next to them: the "proximity" principle (*"the physical distance separating people in the workplace, and the likelihood that they will communicate about their work")* (Coburn, Choi, & Mata, 2010). This often leads to social networks that are limited and homogeneous and that largely focus on grade-level colleagues. When it comes to a specific topic, teachers tend to form ties with colleagues who have expertise on that specific topic (Coburn et al., 2010). Staman, Visscher, and Luyten (2014) found that the academic coach and the school leader are the persons most knowledgeable about the interpretation of student outcome data from a student monitoring system and about the types of analyses that can be conducted using that system. In the Dutch context, the academic coach advises teachers on how to deal with students with special needs, gives instructional advice to the teacher, or tries to find external help. Based on their role within the school team, it was expected that teachers will reach out most to the academic coach for discussing student achievement and the goals to be accomplished. This might lead to unequally divided relationships within a team, where the "expert" within the team has most power and decides which information to share.

Since many authors (Atteberry & Bryk, 2010; Coburn & Russell, 2008; Finnigan & Daly, 2012; Penuel & Riel, 2007) stated that reform initiatives are more successful in schools that have more developed social networks, it seems that social networks characterized by low collaboration and unequally divided relationships within the school team would not be a solid foundation for comprehensive school reform.

A reform initiative could influence the collaboration patterns of a school team, but only a few studies have looked into the *transformation of social networks* within schools, especially where such development is the result of school improvement interventions (Moolenaar, 2012). In their case studies of four elementary schools during the implementation of a new mathematics curriculum, Coburn et al. (2010) found that as a result of the intervention in which teachers were encouraged to collaborate, networks became denser and more diverse. Furthermore, during reform implementation, there was a desire among teachers to interact with those colleagues perceived as "having relevant expertise." This tendency to interact with experts on implementation reform was also observed in other studies (Atteberry & Bryk, 2010; Coburn et al., 2010). However, in these studies reform was aimed at training specific staff within the team to become experts.

Problem Statement

To our knowledge, studies of the effect of an intervention in which the entire team is involved in team network structures are nonexistent. Furthermore, until now the analysis of social networks within schools has mainly been of a cross-sectional kind, has been based on small samples, and includes many case studies. For our better understanding of the role of social networks in school development efforts, longitudinal studies based on larger samples in which the *transformations* of social networks during a schoolwide reform are investigated are needed. Therefore, the current study took a social network perspective to explore how collaboration takes shape in the interactions among school staff as they engage in a schoolwide DBDM reform. This study was guided by the following research question: *What do collaboration patterns within schools at the start of a DBDM reform look like and how do they change during that reform?* In order to answer this research question, first the collaboration patterns at the start of the DBDM reform were explored, and it was also explored whether school characteristics (like the size of the team, the average age of the team members, and the SES of the students in the school) were associated with these initial collaboration structures. Next, the transformations of the social networks during the DBDM reform were studied.

THE DBDM INTERVENTION

Like a number of U.S. interventions (e.g. Boudett, City, & Murnane, 2005; Carlson, Borman, & Robinson, 2011; Love et al., 2008; Slavin, Cheung, Holmes, Madden, & Chamberlain, 2012), the DBDM intervention in this study was a 2-year training course for entire elementary school teams in the Netherlands aimed at implementing and sustaining DBDM in the entire school organization by systematically following the DBDM cycle as shown in Figure 1. For the purpose of this study we focused on collaboration within school teams before and after the first year of the intervention. In Table 1 the outline of the first intervention year is shown.

Table 1. Overview of the First Year of the DBDM Intervention

	Type of meeting	Content
	School leader / school board meeting	Fulfilling practical preconditions and stressing the importance of the role of the school leader/school board
1	Team meeting (full day)	Analyzing test score data from the student monitoring system
2	Team meeting (half day)	Subject matter content – curriculum Individual diagnosis of students' learning needs
3	Team meeting (half day)	Goal setting and developing instructional plans
4	Team meeting (half day)	Instructional plans in practice Monitoring and adjusting instructional plans based on test data from content mastery tests and daily work in class
	School leader / school board meeting	Discussing progress and the goals for the next period (trainer, school leader, and school board)
5	Team meeting (half day)	Team meeting: evaluating standardized test performance data
6	Team meeting (half day)	Collaboration in the school: how to learn from each other by using classroom observations
	School leader / school board meeting	Discussing progress and goals for the next period (trainer, school leader, and school board)
7	Team meeting (half day)	Team meeting: evaluating standardized test performance data

Schools chose one subject to focus on during the first intervention year: mathematics, spelling, reading, or vocabulary. During the first year training year, the four DBDM components (Figure 1) were introduced one by one. The first four meetings were primarily dedicated to acquiring the knowledge and skills for DBDM: using the student monitoring system, analyzing and interpreting test score data, diagnosing learning needs, setting goals, and developing instructional plans. Between meetings 4 and 5 teachers executed their instructional plans in their classrooms. During meeting 5 the DBDM cycle was completed for the first time when the new student achievement data were discussed during a team meeting. The trainers then stressed that these data were supposed to be used for improvement purposes rather than for judging colleagues. The goal was to develop a culture of trust and collaboration in which the school team as a whole felt the responsibility for the performance of their students. The sixth meeting was aimed at teacher peer consultation: providing teachers with the knowledge and tools for observing their colleagues in the classroom and for providing them with feedback based on those observations. In meeting 7 (as in meeting 5) the new student test results were again discussed with the entire school team.

Since it was assumed that teacher collaboration is important for the successful implementation of DBDM, the intervention was offered as a team training. The entire team, including school leaders, academic coaches, teachers, and sometimes also teaching assistants, participated in the project. This collective participation is in line with the professional development literature stating that interaction and collaboration between colleagues is important when implementing and mastering a schoolwide innovation (Timperley, 2008; Van Veen, Zwart, & Meirink, 2011). Moreover, all intervention meetings included collaborative activities, such as activities in which colleagues shared ideas, adjusted performance goals, exchanged teaching strategies with each other, and cooperatively wrote instructional plans.

School leaders and academic coaches were also coached by the trainer to improve collaboration within the team, for example, through allocating time for collaborative activities, organizing team meetings in addition to the training sessions, and encouraging teachers to ask for advice regarding teaching and classroom management strategies.

The training was provided by trainers who had been appointed by the university for this project, and the project was supervised by the first author, who was not directly involved in working with the schools. To ascertain that the training was as much as possible the same across schools and trainers, each meeting had a central topic as shown in Table 1. This topic was the same for every participating school. The content of the meetings was fixed for all schools, the same Power Point slides were used, and the same exercises were done in all schools. Before each meeting the trainers discussed the content for that specific meeting intensively to assure that each of them would present the information in the same way. Because of variation in school teams' prior knowledge, team members' needs, and the subject chosen by a school, the time a trainer spent on a specific topic within a meeting varied somewhat over schools.

Although the content of meetings was very similar across schools, what schools did after the meetings with the information received varied and was influenced by several factors such as the characteristics of the school leader of the school, teachers' attitudes toward the intervention, and the time that could be spent on DBDM.

HYPOTHESES

Since DBDM comprises several components, three social networks related to DBDM were studied: the social network for discussing student achievement, the network for discussing the performance goals that teachers would like to accomplish, and finally, the network for discussing instructional strategies. Since the intervention encouraged school teams to discuss these DBDM issues and consequently aimed to improve the relationships regarding DBDM, it was expected that during the course of the intervention the social network structure would change as reflected by an increased number of DBDM relationships.

We studied which changes occurred during the course of the intervention. Because it proved impossible to have a control group as a counterfactual, we cannot claim causality between the observed changes and the intervention. *Hypothesis 1* reads as follows: during DBDM implementation the number of relationships related to all DBDM topics (reflected by "density") will increase.

DBDM will not only be discussed more, but also in a more intense manner, meaning that teachers have a closer look at their students' achievement, their achievement goals, and instructional approaches, and will discuss these in more detail with their colleagues. Therefore, it was expected that the number of mutual relationships (reciprocity) regarding DBDM would increase during the intervention. *Hypothesis 2*: during the DBDM implementation the number of reciprocal relationships regarding DBDM topics will increase.

Because the intervention was aimed at the entire school team and not just at one person within the team, it was expected that more team members would become knowledgeable about DBDM. We therefore expected that the academic coach would not be the only central person in the network, and that more equally divided DBDM relationships would be found. This was expected to lead to lower centralization measures. *Hypothesis 3*: during the DBDM implementation the network regarding DBDM topics will be less centralized around one or a few influential persons compared to the start of the intervention.

School characteristics such as the number of low-SES students and school size might influence how collaboration patterns are formed. In large school teams, the total number of possible relationships is much larger than in small schools. As a result, the pace of the information flow between the large number of teachers is slower than in smaller school teams. *Hypothesis 4*: in large schools density is expected to be lower.

In schools with more than average low-SES students, student achievement is usually lower (Mullis, Martin, Foy, & Arora, 2012), and teachers in those schools feel a stronger need to work together to improve student achievement. Therefore, it was expected that schools with more low-SES students than average would have more developed networks at the start of the DBDM implementation compared to schools with more high-SES students than average. *Hypothesis 5*: schools with more low-SES students than average will have more developed networks compared to schools with on average more high-SES students.

The average age of the team members might also influence the density of the social networks. Moolenaar (2010) found that older and more experienced teachers are engaged to a lesser extent in work-related discussions compared to their younger colleagues. Spillane, Kim, and Frank (2012) also found that more experienced teachers were less likely to receive advice or information in the school network. It was therefore expected that in—on average—younger team's networks would be more dense. *Hypothesis 6*: in "young" school teams, collaboration regarding DBDM topics will be more dense.

METHODOLOGY

Data for this study were gathered from 41 elementary (K–6) schools in the Netherlands that participated in the project. Data was collected at the start and after 1 year of DBDM implementation. In this section, first the sample and data collection are described, after which the section ends with a description of how the data were analyzed.

SAMPLE

Four selection criteria were used to select the schools for the current study. First, schools had to participate in the intervention with the entire team; 1 school did not meet this criterion (teachers in the infant grades did not participate in the project). Second, the schools had to participate the whole school year. For organizational reasons, 1 school started in January 2013 instead of July 2012 and therefore also was excluded. Furthermore, school teams had to consist of at least six team members, because small teams could influence the network measures too much; 2 school teams were excluded based on this criterion. Fourth and finally, because of their central position, school leaders had to fill out the questionnaire at both measurement occasions. The 5 schools in which this was not the case were excluded as well. After applying the selection criteria, 32 out of 41 schools remained in the sample.

The 32 sample schools were mainly located in urban areas throughout the Netherlands and served a student population ranging from 69 to 545 students aged 4 to 13. Compared to all Dutch schools, participating schools had relatively many students from a lower-SES background, and the average number of students in the participating schools was slightly larger than the national average; this is presumably caused by the exclusion of schools with small teams.

Data was collected from all team members during the first and last meetings of the first intervention year. School teams ranged in size between 8 and 29 staff members. Of 616 elementary school staff members at the start of the project, 594 completed the survey (response rate 96.5%; range 86%–100%). Of 596 staff members present at the last meeting, 546 completed the survey (response rate 92%; range 74%–100%). A matched dataset was constructed that included all staff members from whom data had been obtained at both measurements, resulting in a dataset of 512 respondents and an overall response rate of 89.2%.

Of the matched sample, about 87% of respondents were female, and the age of staff members ranged from 22 to 64 (M=43.9, SD=12.0). Because 2 of the 32 schools were located at two locations, 34 respondents fulfilled the role of school leader, 38 respondents were internal academic coaches, and 412 were teachers. Twenty-three staff members fulfilled other functions; most of them were teaching assistants.

Table 2. Sample Characteristics of Schools (*N*=32) and Individuals (*n*=512)

Individual level		N	%
Gender	Male	69	(13.5%)
	Female	443	(86.5%)
Experience in elementary education	0–3 years	45	(8.8%)
	4–10 years	147	(28.7%)
	> 10 years	318	(62.1%)
	Unknown	2	(0.4%)
Role	School leader	34	(6.6%)
	Deputy school leader	5	(1.0%)
	Academic coach	38	(7.4%)
	Teacher Kindergarten grades (age 4–6)	100	(19.5%)
	Teacher lower junior grades (age 7–9)	148	(28.9%)
	Teacher upper junior grades (age 10–12)	164	(32.0%)
	Other (e.g. remedial teacher, teacher assistant)	23	(4.5%)
Educational level	University degree	12	(2.3%)
	Higher vocational education	442	(86.3%)
	Intermediate vocational education	51	(10.0%)
	Other	7	(1.4%)
School level			

Individual level		**N**	**%**
School size	Small (<150)	7	(21.9%)
	Medium (150–350)	18	(56.3%)
	Large (>350)	7	(21.9%)
School SES	High	8	(25.0%)
	Medium	18	(56.3%)
	Low	6	(18.8%)
Urbanization	Urban (4 largest cities in the Netherlands)	5	(15.6%)
	Suburban (next 32 largest cities in the Netherlands)	13	(40.6%)
	Rural (smaller towns and villages)	14	(43.8%)

	N	**M**	**Sd**	**Min**	**Max**
Individual level					
Age staff	512	43.9	12.0	22	64
School level					
Gender ratio	32	86.5	7.0	72.7	100.0
Average age staff	32	44.0	4.3	35.5	53.9
School size (students)	32	248.3	112.9	69	545
Team size	32	16.0	5.7	8	29

DATA COLLECTION

Social Networks

To examine the changes in collaboration patterns within the school teams, a quantitative survey method was applied. Participants completed a questionnaire at the start of the intervention, and after 1 year. This method made it possible to generate and monitor collaboration trends during the course of the DBDM intervention. Building on earlier work (Moolenaar, Sleegers, Karsten, & Daly, 2012), three types of network questions reflecting aspects of DBDM were selected for their appropriateness in measuring teacher interactions. For instance, as research on DBDM underlines the importance of discussing student achievement (Visscher & Ehren, 2011) as a first network measure, the prompt "With which colleagues do you discuss *student achievement and progress* at least once a month?" was included. Another important aspect of DBDM involves collaboratively setting achievement goals that teachers would like to accomplish. Therefore, the following network prompt was included: “With which colleagues do you discuss the *achievement goals* you would like to accomplish at least once a month?” Finally, in order to reach established goals, teachers need to choose effective instruction strategies. Sharing and discussing effective instruction strategies with your colleagues is therefore a third important aspect of DBDM. The third network question therefore was: “With which colleagues do you discuss the *instructional strategies* in your *group*/in the *school* as a whole at least once a month?”

A roster technique was used to elicit respondents’ interactions with their colleagues. More specifically, a list of numbers was included that corresponded to a list of all colleagues. For each of these questions respondents were asked to tick the numbers corresponding to the colleagues with whom they interacted; the number of colleagues a respondent could tick was unlimited.

School Characteristics

Besides the network measures, data was collected on team size, the average school SES, and the average age of the team members. School SES (categorized as high, medium, or low) was based on the percentage of students that had been assigned extra “weight” based on parental educational levels indicating low SES.[1]

DATA ANALYSIS STRATEGY

Social Network Measures

For each school the density, reciprocity, and centralization measures were computed, before and after 1 year of DBDM implementation, using the UCINET 6.0 software package (Borgatti, Everett, & Freeman, 2002). The concentration of relationships in a social network (*density*) can range from 0 (no relationships at all) to 1 (all relationships are present). *Reciprocity* (the extent to which relationships in a network are mutual) also can range between 0 (no reciprocal relationships) and 1 (all relationships are reciprocal). *Centralized* networks finally are centralized around one or more “popular” actors. Centralization of networks ranges from 0 (the relationships are dispersed equally among all network actors) to 1 (the network is completely centralized).

This resulted in nine dependent variables: density, reciprocity, and centralization of all three network types.

Testing the Hypotheses

Since the three network types (achievements, goals, and strategies) together were considered to form the basis of DBDM and were measured twice within a school team, multivariate linear regression was conducted with six dependent variables. For each of the network measures (density, reciprocity, and centralization) a multivariate linear analysis was conducted using the Car package in R (Fox, Friendly, & Weisberg, 2013). The explanatory variables team size, school SES, and average team age were used to explain differences in network measures between schools. The factor variables "time" and "network type" were used to explain differences between measurements within a school over time. The network measures were observed at the beginning and at the end of the first intervention year, which corresponds to a repeated-measure design with two measurements for each network type.

After conducting the multivariate linear analysis and defining appropriate contrast matrices, multiple hypotheses were tested to identify differences between network measures across schools, across network types, and over time. The hypotheses were tested using the multivariate test statistic, Wilk's Lambda, which is known to be F-distributed under the null hypothesis. The shortened R script of the analyses is presented in the Appendix; extended scripts are available on request from the first author.

RESULTS

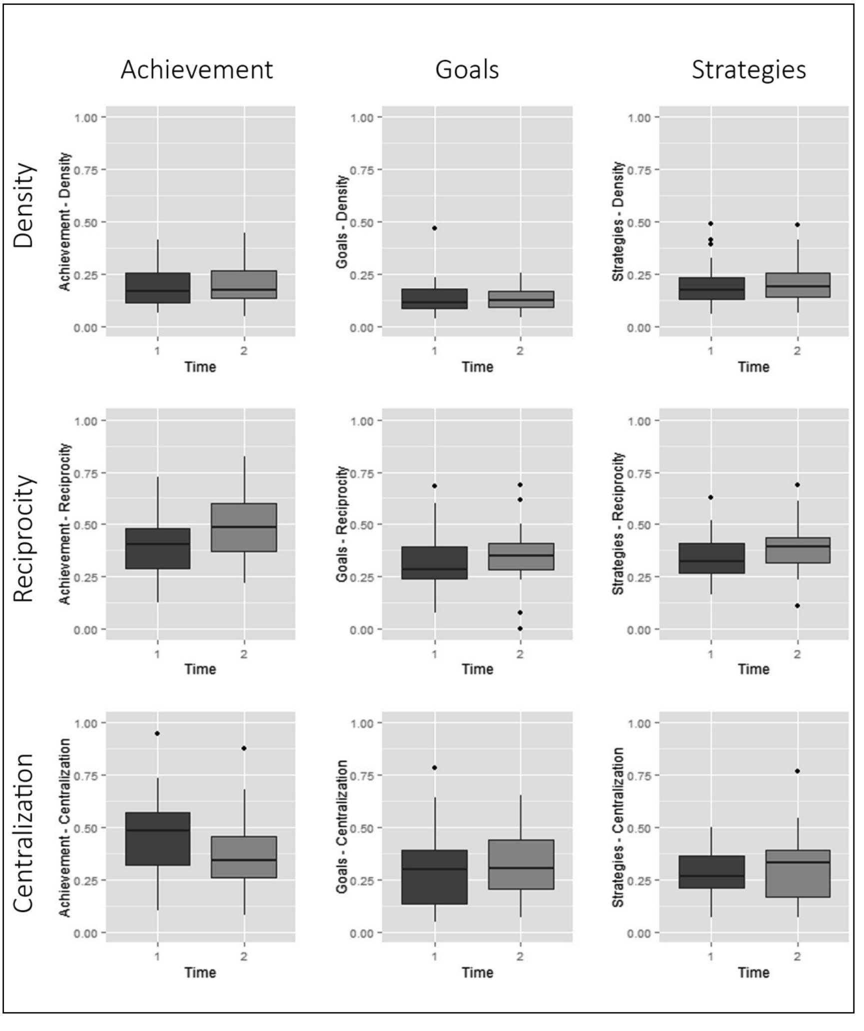
WHAT COLLABORATION LOOKED LIKE BEFORE THE DBDM IMPLEMENTATION

Before answering the hypotheses, we studied what collaboration looked like before the DBDM implementation. Figure 2 depicts boxplots of network measures (density, reciprocity, and centralization) per network type (achievement, goals, instructional strategies), before and after 1 year of DBDM implementation.

Means and standard deviations per network measure, per network type are shown in Table 3. Prior to the DBDM intervention, "achievement" and "instructional strategies" networks were on average slightly denser than the "goals" networks. Almost 20% of all possible relationships were observed in the "achievement" and "instructional strategies" networks, compared to 14% of all possible "goals" relationships. The significant main-effect of type in the multivariate analysis (Table 4) confirmed this finding. The densities of the three network types differed significantly from each other. Contrasts showed that the number of relationships regarding both "discussing student achievement" and "instructional strategies" was statistically significantly higher than the number of relationships regarding "discussing performance goals."'

On average, the proportion of mutual relationships (reciprocity) was highest at T1 for discussing student achievement (*M*=39.9, *SD*=13.8) and lowest for discussing goals (*M*=31.5, *SD*=13.9). Finally, the results at T1

Figure 2. Boxplots of the three DBDM network types per network measure (density, reciprocity, centralization) before and after 1 year of DBDM implementation (*n*=32)



suggested that networks concerning student achievement tend to be more centralized than networks related to discussing "instructional strategies" and "performance goals." In other words, the former network was more centralized around a few influential teachers, while the latter two networks were more dispersed among staff members.

Table 3. Means (and Standard Deviations) of the Three DBDM Network Measures at T1 and T2 (*n*=32)

	Achievement		Goals		Strategies	
	T1	**T2**	**T1**	**T2**	**T1**	**T2**
Density	18.7 (8.9)	19.6 (9.2)	13.7 (8.1)	13.0 (5.7)	19.6 (9.9)	21.1 (10.5)
Reciprocity	39.9 (13.8)	48.4 (13.8)	31.5 (13.9)	35.6 (13.3)	34.5 (10.4)	38.6 (11.5)
Centralization	45.5 (19.1)	37.3 (18.3)	30.0 (18.7)	34.8 (19.7)	28.5 (11.9)	31.5 (15.5)

HOW COLLABORATION DEVELOPS DURING THE DBDM INTERVENTION

The first three hypotheses were about the transformation of the networks during the DBDM intervention. It was expected that density and reciprocity increased, and that centrality decreased. Changes in density, reciprocity and centralization were tested (the results can be found in Table 4). The number of relationships (density) remained stable during the DBDM implementation. For at least one of the network types the number of reciprocal relationships changed during the intervention. By testing contrasts, we found that the number of reciprocal relationships for the "achievement" network increased significantly (β=.09, F=.69, p=<.001), but not for the "goals" or the "instructional strategies" networks. Furthermore, Table 4 shows a significant time*type interaction effect for centralization; contrasts showed that centralization decreased for the "student achievement" network (β=-.08, F=.77, p=.01), but not for the "goals" or the "instructional strategies" network.

Table 4. Multivariate Tests on Predictors of DBDM Network Measures (Density, Reciprocity, Centralization)

	Density			Reciprocity			Centralization		
Effect	**Λ**	**F (df1, df2)**		**Λ**	**F (df1, df2)**		**Λ**	**F**	
Intercept	.07	366.09 (1,28)	**	.05	591.5 (1,28)	**	.08	309.7 (1,28)	**
Between schools									
Team size	.42	39.29 (1,28)	**	.96	1.03 (1,28)		.81	6.56 (1,28)	*
School SES	.98	.53 (1,28)		1.00	0.02 (1,28)		.86	4.67 (1,28)	*
Average age	.96	1.17 (1,28)		.97	.71 (1,28)		.76	8.91 (1,28)	*
Time									
Time	.98	.43 (1,28)		.71	11.25 (1,28)	**	1.00	.00 (1,28)	
Time*Team size	1.00	.07 (1,28)		1.00	.01 (1,28)		.97	.85 (1,28)	
Time*School SES	.99	.28 (1,28)		.99	.33 (1,28)		.98	.71 (1,28)	
Time*Average age	.97	.92 (1,28)		.98	.46 (1,28)		1.00	.00 (1,28)	
Type									
Type	.25	41.54 (2,27)	**	.53	12.06 (2, 27)	**	.33	27.25 (2, 27)	**
Type*Team size	.72	5.14 (2,27)	*	.95	.74 (2, 27)		.92	1.21 (2, 27)	
Type*School SES	.91	1.32 (2,27)		.87	2.09 (2, 27)		.82	2.97 (2, 27)	
Type*Average age	1.00	.04 (2,27)		.98	.27 (2, 27)		.91	1.26 (2, 27)	
Type*Time	.88	1.87 (2,27)		.94	.93 (2, 27)		.66	6.88 (2, 27)	**

*<.05; **<.01

HOW SCHOOLS' BACKGROUND VARIABLES INFLUENCE DBDM COLLABORATION

In order to test hypotheses 4, 5, and 6 about the background variables influencing DBDM collaboration, the explanatory variables team size, school SES, and average age of the team were included in the model. The main effects in Table 4 of these explanatory variables on the three network measures explained differences between schools. For all network types the size of the team had a negative effect on density. Contrasts showed that the size of the effect was largest for "discussing instructional strategies" (β= -.025, *F*=.49, *p*=<.001) and "student achievement" (β= -.024, *F*=.40, *p*=<.001), and slightly smaller for "discussing goals" (β= -.016, *F*=.51, *p*=<.001). This explained the significant interaction-effect between network type and team size in Table 5. The findings suggested that the larger the team, the smaller the proportion of actual relationships. Furthermore, team size influenced centralization: in larger teams the number of relationships was more equally dispersed.

A small significant effect of school SES was found for centralization. Contrasts showed that this effect only obtained for the "goals" networks (β=.21, *F*=.77, *p*=.01). This means that the higher the proportion of low-SES students in the school, the more centralized the network. In other words, in schools with many low-SES students relationships regarding "discussing goals" were more centralized around one or a few influential persons.

The average age of the team was found to have a significant effect on centralization: the higher the average age, the more equally dispersed the relationships in the network. This effect was the same for all network types.

Background variables team size, school SES, and average age did not influence the *development* of the collaboration patterns.

CONCLUSIONS AND DISCUSSIONS

Many scholars in the field consider a collaborative school culture as a precondition for the successful implementation of a (DBDM) reform project. However, few researchers have studied the impact of such a project on collaboration patterns within schools. In the present study, the transformation of DBDM collaboration patterns during a DBDM intervention were investigated. This was done by studying the density, reciprocity, and centralization of three DBDM networks in 32 elementary schools in the Netherlands.

Table 5. Study Hypotheses, Results, and Findings

Hypotheses	Results	Findings
Hypothesis 1: during the DBDM implementation the **number of relationships** regarding all DBDM topics (reflected by 'density') will **increase**.	Not supported	No significant effect for all three network types (discussing student achievement, goals, and instructional strategies).
Hypothesis 2: during the DBDM implementation the number of **reciprocal relationships** regarding DBDM topics will **increase**.	Partially supported	The number of reciprocal relationships increases for the **student achievement network**, but not for the goals and for the instructional strategies network.
Hypothesis 3: during the DBDM implementation the network regarding DBDM topics will be **less centralized** around one or a few influential persons compared to the start.	Partially supported	Centralization decreases for the **student achievement network**, but not for the goals and instructional strategies network.
Hypothesis 4: in schools with **large teams** density is **lower**.	Supported	The number of team members influences the proportion of relationships regarding DBDM (density): the larger the team, the lower the density.
Hypothesis 5: schools with **more low-SES students** than the average, will have **more developed networks** compared to schools with on average more high-SES students.	Not supported	No significant effect.
Hypothesis 6: in **young** school teams collaboration regarding DBDM topics is denser.	Not supported	No significant effect.

Results of hypotheses testing are summarized in Table 5. In order to test our hypotheses, first the collaboration patterns before the intervention were studied. Since schools chose to participate in a DBDM intervention themselves, it was expected that interaction regarding DBDM topics such as discussing "student achievement," "goals," and "instructional strategies" was not everyday practice, and that this would be reflected by low density, low reciprocity, and high centralization. Our findings show that in terms of discussing "student achievement" and "instructional strategies," approximately 20% of all potential relationships had actually been formed, while "achievement goals" were little discussed. In all DBDM networks, not even one fifth of all potential relationships were formed. This is in line with our expectations, but also problematic, since such a sparse network could hinder the development of DBDM within the school.

Furthermore, the percentage of reciprocal relationships was less than 40% for all three DBDM networks, indicating that fewer than half of all possible relationships were reported by both actors. Since reciprocal relationships are associated with the transfer of complex knowledge (Kilduff & Tsai, 2003), we consider this level of network reciprocity to be low. Since DBDM asks team members to work together to improve student achievement, this low level of reciprocity might reduce the effectiveness of DBDM.

Finally, it was expected that the initial DBDM networks would be very centralized, due to the expected central position of the academic coach in the network. Results show that this is especially true for the "achievement" network, suggesting that those relationships in which student achievement is discussed are organized around one or a few influential persons (probably the academic coach or coaches) in a school. However, the "instructional strategies" network was less centralized. An explanation for this might be that teachers discuss these instructional strategies not (only) with a person who they consider to be an expert, but also with teachers in the same grade level or in the classroom next door. Current analyses address only the school level; further analysis at the individual teacher level would be needed to confirm this.

Even though we cannot claim that the DBDM networks transform as a result of the DBDM intervention, the observed network changes are interesting and can provide a basis for future studies that allow causal claims. It was expected that collaboration regarding DBDM topics like "discussing student achievement," "discussing performance goals," and "discussing instructional strategies" would grow during the intervention. This was expected to be reflected by increased numbers of relationships (hypothesis 1), increased numbers of reciprocal relationships (hypothesis 2), and a decreased centrality of the network (hypothesis 3); the latter would mean that relationships are dispersed more equally within the team.

Hypothesis 1 is not confirmed. Growth in the number of DBDM relationships is not observed. The number of *mutual* relationships staff members reported did increase for the "student achievement" network but did not increase for the "goals" or the "instructional strategies" networks (partial support hypothesis 2). This might imply that compared to the start of the intervention, more complex knowledge regarding student achievement is shared now between staff members. Remarkably, centralization in both the "goals" and the "strategies" networks remained stable. In turn, in the "student achievement" networks, relationships became more equally divided (hypothesis 3 partially supported).

In sum: collaboration within school teams changes during the implementation of the DBDM reform to some extent. Although the number of relationships within the network remains stable, DBDM collaboration changes within the school teams, reflected by increased reciprocity (more mutual relationships between school staff members), and decreased centrality (more dispersed relationships within school teams), especially for the "achievement network."

As far as the nature of the collaboration is concerned, the study points to the fact that changes during the DBDM intervention were especially found with respect to discussing "student performance." By contrast, collaboration with respect to "performance goals" and "instructional strategies" is not influenced much during the DBDM intervention. It seems that learning about the possibilities and use of student performance data went together with the strongest changes in teacher collaboration. Setting goals cooperatively and discussing and adapting instructional approaches both seem to change less easily. The utilization of student performance data throughout the school is something quite new and revolutionary for Dutch teachers and schools; instructional decisions are considered to belong to the discretion of individual teachers.

Great variability is found between the school networks. It was expected that school characteristics such as the proportion of low-SES students in schools, average team size, and the average age of the team members influenced the DBDM networks. However, multivariate analysis shows no effect either of SES (hypothesis 5, rejected) or of average team age (hypothesis 6, rejected) on the density of the networks. Average age does have an effect on centralization: the older the team, the more equally dispersed the relationships in the network. Possibly, staff members in teams with less experienced, younger teachers tend to reach out more to a DBDM expert, compared to staff in teams with more experienced (older) teachers. School SES does influence centralization, but only for the "goals" networks: in schools with a high percentage of low-SES students, networks were more centralized around one or a few central persons. An explanation for this finding remains unsure.

Finally, the size of the team is related to collaboration density: the smaller the team, the denser the network (hypothesis 4, confirmed). In larger teams, there might be fewer opportunities to share knowledge and expertise with each other since large teams have more links through which the information has to flow. Moreover, the question is whether it is possible and desirable to discuss DBDM topics in a team wide way in large teams. In small teams with only one or two teachers per grade, the need to share DBDM knowledge and skills with the entire team is stronger, compared to a school with more than four or five teachers per grade. In such a large school, subgroups of teachers within the same grades are often formed in order to discuss DBDM topics.

LIMITATIONS AND AREAS FOR FUTURE RESEARCH

Although the findings of this study provide insight into the changes that occurred during a DBDM intervention, it is not correct to claim that these changes occurred *due to* the intervention since all respondents participated in the DBDM intervention, and a control group could not be included in this research. Further research is needed to clarify the changes in networks as a result of DBDM interventions using longitudinal *experimental* designs.

Furthermore, the study deals with the perceptions of school team members about their interactions with colleagues. These perceptions may change due to the intervention, which might influence their interpretation of the network questions. For example, the participants were familiar with the three DBDM subjects at the start of the training, but due to the training the interpretation of "discussing student achievement" may have differed at T2 from the interpretation at T1. Teachers may have talked about their student outcomes at T1, but the content of those conversations may differ after 1 year of intervention. This might explain why network density did not change during the intervention. In future research, it will be important to not only study whether teachers talk with each other about DBDM topics, but also to investigate the frequency and the nature of such interactions.

Based on the literature (both from organizational science and from educational science) we assumed that the ideal DBDM network would be dense, decentralized, and reciprocal. However, this study does not confirm this. It could, for example, be argued that a network centralized around one or two data experts is preferable for sharing data-use knowledge (Marsh et al., 2015). In order to obtain a better understanding of "good" collaboration in the context of DBDM, in a follow-up study the relationships between network characteristics and student achievement will be examined. Hopefully this relationship will also be studied more in other research projects. Furthermore, to better understand network changes (e.g., why the "strategies" and "goals" networks become more centralized), it would be interesting to study the network measures at the *individual* staff member level. This might, for example, provide insight into the role of experts such as the academic coach or the school leader within the team. To do so, longitudinal network analysis using actor-oriented statistical models for network evaluation (Snijders, 2001, 2005; Snijders, Steglich, Schweinberger, & Huisman, 2007) has much potential. Such an advanced longitudinal analysis of social networks would also enable exploring whether changes in relationships over time are different for different positions in a team. Several authors (Datnow, 2011; Levin & Datnow, 2012; Moolenaar et al., 2010) suggest that the school leader can play an important role in DBDM. Centralization of school leaders within a team might change as a result of a DBDM intervention. Further analysis of the current dataset could give more insight into changes in networks related to the various positions within school teams.

To conclude, this first longitudinal study of its kind looking into the transformation of social networks during a school improvement intervention contributes to the knowledge base of social network theory within the context of schools. It indicates that networks within school teams do not only influence reform, but also that a reform can improve networks. Other similar reform initiatives should therefore consider including activities that promote collaboration among school staff during the reform.

NOTES

1. Students are assigned extra "weight" if their parents are from a lower educational background. Students can get an extra weight of 0.3 (maximum parental educational level: lower vocational education), or 1.2 (maximum parental educational level: primary education, or special needs education). Schools receive additional funding based on student weights as it is assumed that schools with students with student weight have a more difficult job to do.

APPENDIX

R Script of the Multivariate Linear Analysis Using the Car Package and Contrast Matrices to Test Hypotheses

```
#——————————————————————————————————————————#
# Shortened R script of the multivariate linear analysis using the Car package #(Fox, Friendly & Weisberg, 2013) and contrast matrices to test hypotheses
#——————————————————————————————————————————#

## Test de within-subject factors type and time (using the Car package)
manova.centr<-Anova(mod.centr, idata=idata, idesign=~Type*Time, test.statistic="Wilks",Type=3)

# The TestContrast() function can be used to test user-defined contrast(s)

TestContrast <- function(Y,X,B,L,P){
 library(Matrix)
 # Y: dependent variables
 # X: independent variables
 # B: estimated effects
 # L: hypotheses (contrasts) on rows of B (between-subjects)
 # P: hypotheses (contrasts) on columns of B (within-subjects)

# hypothesis : LBP = 0

# Compute error matrix (unexplained variance)

E <- matrix(t(Y)%*%Y - t(B)%*%(t(X)%*%X)%*%B,ncol=ncol(Y),nrow=ncol(Y))
EP <- t(P)%*%E%*%P

dum <- solve(L%*%(solve(t(X)%*%X))%*%t(L))
dum1 <- L%*%B%*%P
H <- matrix(t(dum1)%*%dum%*%dum1,ncol=ncol(P),nrow=ncol(P))

#Construct Wilks
testteller <- det(EP)
testnoemer <- det(H+EP)
test <- testteller/testnoemer
```

```
## q :: number of columns in predictor X used in constructing contrast

   #m <- ncol(Y)
   #s <- (ncol(X)-1)- q + 1
   m <- min(ncol(Y),ncol(P))
   s <- (ncol(X)-1) - (ncol(X)-1) + 1

   r <- (nrow(Y)-(ncol(X)-1)-1)-((m-s+1)/2)
   u <- (m*s-2)/4
   if((m**2+s**2-5) != 0){
   t <- sqrt(((m*s)**2-4)/ (m**2+s**2-5))
   } else {
   if((m**2+s**2-5) == 0){
   t <- 1
   } else{
   t <- 0
   }
   }

   testF <- (1-test**(1/t))/(test**(1/t)) * ((r*t-2*u)/(m*s))

   df1 <- m*s
   df2 <-r*t-2*u
   pvalue <- 1-pf(q=testF,df1=df1,df2=df2)

   return(list(test=test,pvalue=pvalue))

  }
  # Test main effect of for example SES:

  L <- matrix(c(0,1,0,0),ncol=ncol(X),nrow=1) # test main effect of SES
  P  <-  matrix(diag(ncol(Y)),ncol=ncol(Y),nrow=ncol(Y))  #No  within
contrasts
  TestContrast(Y,X,B,L,P)
  # Effect of SES, for the goal-network:
  P <- matrix(c(1,1,0,0,0,0),ncol=1)
  TestContrast(Y,X,B,L,P)
  L%*%B%*%P
```

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