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Improving teacher education in the Netherlands: data team as learning team?

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ABSTRACT

Using data in a professional learning community is a promising form of professional development. In this study, we followed a data team of teacher educators, who systematically tried to improve the education of student teachers (by decreasing first year drop-out). By conducting a single case study, we investigated the data team participants' learning in depth. We analysed the team's conversations and investigated the role of the data coach. The results of our observations and interviews showed that the conversations in the data team (1) provided a context for learning; (2) were relevant and slowly reached a higher level of inquiry as the meetings continued; (3) were focused on teaching and learning, although the action plan developed involved general actions and was not so much related to their own teaching and learning; (4) could reach greater depth when the conversations were informed by data.

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1. Introduction

Accountability requires teacher educators to use data to meet stakeholders' demands (Jankowski 2012; Ludlow et al. 2008; Marginson and van der Wende 2007; UNESCO 2013). But can teacher educators use data to improve teacher education? According to Griffiths, Thompson, and Hryniewicz (2014) and Swennen, Jones, and Volman (2010), teacher educators have four different roles: (1) as a teacher, teaching students; (2) as a teacher of teachers, modelling how to teach for student teachers; (3) as a teacher in higher education, meeting its accountability requirements; and (4) as a researcher, researching their own practice. The use of data – defined as 'information that is collected and organized to represent some aspects of schools' (Lai and Schildkamp 2012, 10), takes a different form in each of the four roles of a teacher educator. As a teacher, the teacher educator uses data to inquire into the instructional needs of the students; as a teacher educator, data use involves teaching students to adapt their instruction based on data; as a teacher in higher education, data use involves rendering accounts to stakeholders; and as a researcher, data use involves

systematically trying to improve education. From the perspective that decisions based on data lead to results sooner than decisions based on intuition (Bernhardt 2004), teacher educators (as teachers of teachers) must improve their curriculum as far as teaching student teachers to use data for improvement purposes (eg Italiano and Hine 2014; Keizer et al. 2012).

According to Little (2012), there is a knowledge gap with regard to how teachers engage in the process of using data to improve education. In this paper, we attempt to unravel what happens when a team of teacher educators engage in the process of data use for improvement purposes. In particular, this study focuses on a team of teacher educators who are collaboratively collecting, analysing and interpreting data about a shared problem. The aim was to promote teacher educators' professional learning about data use for school improvement in a college of teacher education.

1.1. About this study

This study took place in a Teacher Education College in the Netherlands. The Teacher Education College prepares primary school teachers in a four-year programme, leading to a bachelor degree (240 European Credits – one European Credit contains 28 hours of study). During the four-year programme students are trained at the college (180 European Credits) and in primary schools during internships (60 European Credits). In the first year, students spend 45 European Credits at the college and 15 European Credits as interns in primary schools. After completion, students are certified to teach in primary schools for children in the age of 4 to 12 years. A current problem in many Teacher Education Colleges in the Netherlands is drop-out. The Teacher Education College in our study wanted to reduce student drop-out, because 18% of the freshmen leave the college during the first year of study, which was higher than the national benchmark (15.7%). A data team (Schildkamp and Poortman 2015) was formed consisting of teacher educators to diagnose the problem, come up with solutions and evaluate the effects. In our study, we used the conversation in the data team to understand how teacher educators' professional learning about data use for school improvement developed.

1.2. Working with data in a professional learning community

Data use can lead to the improvement of education (Campbell and Levin 2009; Carlson, Borman, and Robinson 2011; McNaughton, Lai, and Hsiao 2012). However, educators often do not use data (Schildkamp and Kuiper 2010), but instead make use of their intuition and limited observations (Ingram, Louis, and Schroeder 2004). Therefore, valuable time and resources are lost when new measures are implemented which may not coincide with the students' needs (Earl and Katz 2006). Working with data requires knowledge and skills (Schildkamp and Kuiper 2010) that teacher educators often lack. Professional development related to data use (Desimone 2009; Van Veen et al. 2010) is therefore urgently needed for improving the quality of education.

Professional development is often more effective when it takes place in professional learning communities. Several studies have shown that teacher collaboration in professional learning communities can lead to increased teacher and student learning (Borko 2004; Darling-Hammond 2010; Stoll et al. 2006; Vescio, Ross, and Adams 2008). In a professional learning community, teachers and administrators continuously seek to learn, share what they learn and act on their learning, with the aim of improving education (Sjoer and Meijerink 2015).

A data team is considered to be a special form of a professional learning community, which tries to solve an educational problem in a structured way by using data (Schildkamp and Poortman 2015; Schildkamp, Poortman, and Handelzalts 2015), using the data team method. The method consists of 8 steps: (1) problem definition, (2) formulating hypotheses, (3) data collection, (4) data quality check, (5) data analysis, (6) interpretation and conclusion, (7) implementing improvement measures and (8) evaluation. Research shows that in secondary education, working with a data team can lead to professional development as well as school improvement (Schildkamp and Poortman 2015).

1.3. Learning in data teams

Teacher learning resembles student learning. Student learning benefits from being situated in meaningful contexts, with students actively engaged in the learning process, and collaborating with each other (Borko 2004). Similarly, teacher learning needs to provide possibilities for learning in meaningful contexts with colleagues (eg Borko 2004; Desimone 2009). Characteristics of effective teacher learning include collaboration, follow-up support, coherence with teachers' own professional development goals and with student' learning goals, and be stretched over time (Voogt et al. 2011). Teacher learning in the data team provides these opportunities and is reflected in authentic activities, such as the conversations within the data team. An important aspect of these conversations is the extent to which they are relevant (Henry 2012). Neil and Johnston (2005), and Supovitz and Christman (2003) found that the relevance of the conversations in teams was related to student learning gains. Less-successful teams spend more time on administrative work, student discipline and paperwork, and less time on teacher instruction, student learning and learning materials (Henry 2012). Relevant conversations focus on teaching, learning and materials, and less on the support of teaching, the support of learning and the support of materials or staff issues (Neil and Johnston 2005).

Depth of inquiry is another important aspect of the team's conversations that is related to the students' learning gains. More successful teams (ie teams that achieve higher student learning gains) employ more higher level thinking skills (Achinstein 2002; Stokes 2001) and have conversations with considerable depth of inquiry. The depth of inquiry in a data team can be described as an inquisitive attitude on the part of its members, aimed at developing new knowledge and taking action based on data, while critically reviewing each step of the procedure (Henry 2012). The conversations should reflect reasoning, listening and underlying assumptions. These are not only fundamental for developing steps for improvement, but also contribute to the construction of team-level and individual knowledge (Ikemoto and Marsh 2007), and thereby contribute to learning.

Learning to use data is often associated with specific skills, such as data collection and data skills. However, studies (eg Marsh 2012; Schildkamp and Poortman 2015) have shown that being able to use data for improvement requires much more than being able to collect, analyse and interpret data. Data use also entails collaborating by having relevant conversations based on data, and being able to develop and apply new knowledge in one's own context. Therefore, the concepts of relevance of conversations and depth of inquiry can be used as indicators for learning related to data use for improvement.

Learning is one of the hierarchical levels of effects in Kirkpatrick's evaluation model for evaluating professional development (Kirkpatrick 1960). According to these authors,

professional development (eg in data teams) must lead to learning, before one can expect changes in behaviour. Kirkpatrick distinguishes four hierarchical levels of effects:

- Reaction: The measure of affective response to the quality of professional development;
- Learning: The (extent to which) learning takes place as a result of professional development. In this study, this pertains to the relevance of conversations and depth of inquiry;
- Behaviour: The (extent to which) knowledge and skills gained in the professional development programme are applied on the job;
- Effects: The (extent of) impact the training has on broader organisational goals and objectives.

In this study, we focus on the first two levels (the reaction and learning levels). Kirkpatrick's approach is a useful model for evaluating professional development outcomes (Holton 1996). By itself, the Kirkpatrick model is unlikely to guide educators in making a full evaluation of their educational programme (Bates 2004). The model does not consider data that shed light on why a programme works, unless more data are available and analysed in relation to factors such as the complexity of the organisation, the training and its design, and the individual members participating in the professional learning community (Frye and Hemmer 2012).

1.4. The data coach

To develop the skills the team members require, a data coach supports the data team (Cantrell and Hughes 2008; Neuman and Cunningham 2009). This coach supports the team by leading the participants through the data team procedure, which builds data competencies (Love et al. 2008, 20). Lachat and Smith (2005) divided the role of a data coach into a coaching role versus an expert role. As a coach, the data coach helps the data team to function (eg by preparing the agenda) and also models inquiry. As an expert, the coach shares his or her knowledge and skills with the data team (eg supporting the data team in carrying out data analyses).

1.5. Research questions

As stated above, one way to assess the value of a data team as a form of professional development is by applying Kirkpatrick's evaluation framework for professional development activities (Kirkpatrick 1960). Kirkpatrick identified four levels of effects: reactions (the measure of satisfaction), learning (the extent of learning that occurred), transfer (the extent of changed on-the-job behaviour) and effects (the extent of changed outcomes). In this study, we focus on the first two levels (the participants' general reaction and learning). To gain in-depth insight into how the data team contributes to the professional development of its members, three questions were studied:

- (1) How do members experience their participation in a data team? (Reaction level.)
- (2) What are the learning effects for data team participants? (Learning level.)
 - (a) What is the relevance of the conversations in the data team?
 - (b) What is the depth of inquiry of the conversations in the data team?
- (3) What role does the data coach play in supporting the data team?

2. Method

2.1. Research method

The case study approach was used to investigate a single case of a data team as a form of professional development in teacher education (Savin-Baden and Major 2013). First, the case study is a single-case study in which the data team is the case, and the team meetings and the data coach contributions are the units of analysis (Yin 2014), within the context of the teacher education college. We used one case because the data team as a human system can provide us with insights into how the conversations in the data team contribute to the professional development of the data team members. Second, the case study refers to an exploratory approach, to clarify the relationship between what happens on the reaction and learning levels and data team members' professional development (Yin 2014). By analysing the conversations, we were able to gain insight in ways that are not always susceptible to quantitative analysis (Cohen, Manion, and Morrison 2007). And finally, as a written case, the study provides a unique example of real people in real situations, enabling readers to understand the ideas behind the use of data for professional development more clearly than simply by presenting them with abstract theories or principles (Cohen, Manion, and Morrison 2007, 253). One consequence of studying real people in real situations is that we used quotes to show what happened in the data team. We wanted the quotes to stay as close as possible to the observations of data team members, and we transcribed their spoken language into written language.

In carrying out the case study, the researcher in this study was also the data coach (participatory research). In this way, we were able to gain an insight into both causes and effects of the role of the data coach as related to team members' learning and experiences, insofar as it was necessary for the data coach to actively contribute to the data team process (Cohen, Manion, and Morrison 2007).

The choice of a case study method was a response to Little's (2012) call for micro-process studies, which require close attention to patterns of on-the-ground interaction. By 'zooming-in' to the interactions that occur between actors, we contribute to a programme of research on data use and school improvement and we can expose aspects of practice that otherwise remain opaque. These dynamics of practice are also likely to prove salient in accounting for the evolving nature and consequences of 'data use' in schools and districts (Little 2012, 110).

Our case study approach enabled us to 'zoom-in' and obtain a deeper level of understanding of the first two levels of Kirkpatrick's evaluation model (Kirkpatrick 1960): satisfaction with the professional development in the data team and how learning occurred in the team in terms of the (changes in) relevance of the conversations and depth of inquiry. Moreover, the case study approach enabled us to 'zoom-in' on the role of the data coach. Although this was time-consuming, capturing the entire conversations of the team provided much greater depth of insight than we could have achieved using observation protocols or field notes alone.

2.2. The data team

The participants in the data team were recruited as result of a presentation about the use of data to improve educational quality at the teacher education college organised by the management.

Five teacher educators volunteered to participate after this presentation, and an additional two participants (a tutor and the manager in charge of student drop-out) were asked to take part by management. Five teacher educators, one tutor and a manager participated in the data team (Table 1). The manager in charge of student drop-out participated from a distance, gave the green light for working with a data team and helped with formulating the problem statement. The data coach/researcher was attached to the college as a lecturer.

The data team met 11 times between December 2011 and July 2012 (Table 2).

2.3. Instruments and data analyses

The conversations at all the data team meetings were observed and audiotaped, and the interviews were also audiotaped (Tables 3 and 4). Interviews were conducted by the data coach with all of the data team members, at the middle (March 2012) and end of the data team meetings (July 2012). Both interviews consisted of the same questions and were related to the participants' reactions, the level of learning and the role of the data coach. The researcher also kept field notes. In the notes, the researcher reflected on how the data team functioned and the role of the data coach. Furthermore, artefacts were collected (ie materials used by the data team, such as the raw and analysed data used during the meetings; the instruments used to collect data.)

Table 1. Data team members.

Respondent	Function	Age (at the start of the data team)	Years of teaching experience	Years of experience at the college
1	Teacher pedagogy/ educational science	52	25	4
2	Teacher drama & dance	38	12	2
3	Teacher pedagogy/ educational science	31	9	6
4	Teacher ICT	35	4	4
5	Tutor	53	27	27
6	Teacher visual art & design	40	13	13
	Mean (standard deviation)	41.5 (8.26)	15 (8.30)	9.3 (8.63)

Notes: The F in F1, F2, F3, and F4 stands for a female data team member. M in M1 and M2 stands for a male data team member.

Table 2. Overview of the data team meetings: (number of) members present, and the data team activity during the meeting.

Meeting	Number of members present	Activity (1)
1	6	1, 2
2	6	1, 2
3	4	3
4	6	3, 4
5	4	3
6	5	1, 2, 3
7	4	4, 5, 6
8	5	5, 6, 7
9	4	5, 6, 7
10	6	7
11	6	7

Notes: The activities in the meetings followed the steps of the data team method: (1) problem definition, (2) formulating hypotheses, (3) data collection, (4) quality check, (5) analysis, (6) interpretation and conclusion, (7) implementing improvement measures, (8) evaluation.

Table 3. Overview of instruments in relation to the sub-questions.

	Observations	Interviews	Field notes	Artefacts
Effects at the reaction level: How do members experience their participation in a data team?	X	X	X	X
Effects at the learning level: What is the relevance of the conversations in a data team?	X		X	
What is the depth of inquiry of the conversations in the data team?	X		X	
What role does the data coach play in supporting the data team?	X	X	X	X

Table 4. Overview of the themes, codes, source and code descriptions (1).

Research question	Source	Code	Code description
Relevance	Neil and Johnston 2005	Teaching, student learning, and materials Supporting teaching, learning, and materials	Conversations related to teaching, student learning and learning materials; Conversations related to the support of teaching, the support of student learning and the support of learning materials;
Depth of inquiry	Henry 2012;	Staff issues	Conversations related to staff issues;
		Considerable depth	In the discussion, all members were sharing ideas and beliefs with checking the facts All data team members sharing ideas and beliefs, without fact checking
		Average depth	Several data team members are involved in the discussion, with some exchange of ideas and beliefs, without fact checking
		Some depth	The data team discussions are without any exchanges of ideas/beliefs, without fact checking
Expert role	Lachat and Smith 2005	Expert	The data coach, as an expert, carries out activities that show the data team members how to carry out the activities on their own, how to collect the data and so forth;
Guide role		Coaching	The data coach carries out activities to support showing the data team how to work with data, and activities to encourage the data team in the process of working with data

Note: In order to measure relevance and depth, each transcript was divided into chunks each ten lines long. Each section was then coded for relevance and depth.

The observations, interviews, field notes and artefacts were analysed using Quality Data Analysis (QDA) (Lewins and Silver 2007). The codes were based on theories of teacher learning, especially the relevance of the conversations (based on Neil and Johnston 2005) and on depth (based on Henry 2012) Table 4. Conversations related to teaching, student learning and materials were coded with relevance and conversations related to other subjects (for instance about the minutes) were coded with no relevance. Before coding on depth, the transcripts we divided in portions of 10 lines each. Each 10-line portion was coded with no depth, some depth, average depth of with depth. Fragments without any exchanges of ideas/beliefs, without fact checking, were coded with 'no depth'. Fragments with some exchange of ideas and beliefs, without fact checking, were coded with 'some depth'. Fragments with all members sharing ideas and beliefs, without fact checking, were coded with average depth. And, finally, fragments where all members sharing ideas and beliefs with checking the facts, were coded with 'depth'. The mean depth was calculated by assigning 1 to fragments of no depth, 2 to those coded as having some depth, 3 to those coded as

having average depth and 4 to those coded as having considerable depth. The overall mean depth for the meeting were based on the total value of the coded fragments for that meeting, divided by the total number of coded fragments related to depth. The role of the coach was coded based on Lachat and Smith (2005). Fragments where the data coach carried out activities, which showed the data team members how to carry out the activities on their own, how to collect data and so forth, were coded as 'the expert-role'. Fragments of the data coach carrying out activities showing the data team how to work with data, and activities encouraging the data team in the process of working with data, were coded as 'the coach-role'.

The data were coded using the pattern-matching strategy (Yin 2014) whereby in three successive rounds, information from the case was related to the theoretical categories of relevance, depth and the coach's role, respectively. Uncategorised data were not used. Before finally removing this data, we attempted to categorise these data in an additional category in order to ensure that the discarded data did not contain any valuable information. Finally, the data from observations were matched to data from interviews, artefacts and notes.

2.4. Validity and reliability

Constructs from the literature were used to formulate interview questions and to code the transcripts (Poortman and Schildkamp 2011). The interview questions, which were based on prior research (Kirkpatrick 1960; Lachat and Smith 2005; Schildkamp and Kuiper 2010, eg: Looking back at the data team meetings, what is your reaction on the data used in the data team?), were first tested and adjusted where needed. A fellow researcher also coded 10% of all transcripts. The inter-rater reliability was calculated and resulted in a high Cohen's kappa of 0.79. In order to further ensure the reliability of the study, the observations and interviews were audio-recorded, QDA was used to code and analyse the data, and finally, method and data triangulation were used.

2.5. Case: preventing student teachers from dropping out during the first year

The purpose of the data team was to reduce the amount of drop-out:

We will explore the reasons for the (potential) drop-out rate among freshmen in full-time training, because we want to know why students leave in order to support them during their study by dealing with the top 3 reasons we can change for the better to prevent them from dropping out. (Data team meeting 1, F3)

The data team formulated hypotheses about group atmosphere, educational background, gender, and learning and planning skills. First, an existing exit survey was adapted for use in investigating the reasons for student drop-out, a digital questionnaire with both open and closed (Likert-scale) questions (response rate 23%, $N = 18$). Second, a study progress report was used, with the number of credits per student per course and per period, and the total number of credits accumulated. Finally, the team developed a short survey (via email) among the tutors about the cause of the increase in the number of credits for a selected group of students (100% response rate, $N = 7$). The quality of the adapted exit survey was monitored by means of a trial administration. And, comparing the study progress report with other reports assessed the quality of the study progress report. The results from the exit survey and the tutor survey were analysed in frequency tables, and the study progress report results were analysed with an independent samples t -test to reject or endorse the

hypotheses about group atmosphere, educational background and gender. The hypotheses related to group atmosphere, educational background and gender were rejected and were not found to influence drop-out. The next hypothesis focused on study success for different parts of the programme. These data show per student which parts of the programme were completed successfully in terms of European Credits (one year has 60 European Credits). The data showed that students completed on average 5 (of the 14) European Credits (35.7%) in the first quarter of the freshman year, 16 (of the 30) European Credits (53.3%) in the second quarter, and 31 (of the 45) European Credits (68.9%) in the third quarter of the freshmen year. Based on these data, the data team concluded that students were insufficiently challenged to study in the beginning of their programme, which was related to drop-out. This led to the following improvement measures: first, the data team gave a presentation to the entire teaching staff about the progress students had made over the year and the conclusions from their investigations. Second, they proposed a course for students that would be focused on developing study skills, guiding the students to learn independently in the second period (of four) of the year.

3. Results

3.1. *Effects at the reaction level*

In the interviews, six of the seven members experienced the data team procedure as meaningful and praised the possibility of handling a problem thoroughly. Some members even indicated that they really needed the structure provided by the data team procedure, and that they wished to change the way they had been working so far to start using data to improve education (eg Ruffner 2008). For example, one of the respondents indicated:

The times when we had the luxury of fooling around are over. When I look at last year's number of applicants, something needs to happen ... We need to be sharp and ensure things (data) are in order. (Interview with data team member 1, July 2012.)

This also points to the increased emphasis of data use in teacher training colleges. Teacher educators are expected to use data to improve their education and are held accountable for doing so (eg Plecki, Elfers, and Nakamura 2012). One data team member had hesitations about the meaningfulness of the data team method. He/she thought the method was useful, but that it was also circuitous and did not add anything new. The question here is if for this respondent, the data team procedure was really not new, or that he/she did not fully grasp the meaning of it and/or was perhaps resistant to investing time in learning. Three of the seven members did appreciate the chance to learn about data use, the data team procedure, and how to conduct research in their own organisation. A teacher educator saw it as an opportunity to practise their research skills:

Doing a bit of research again, for a while. Analysing data. I really liked that ... it [following the procedure] is a nice way of refreshing your knowledge and abilities. (Interview with data team member 2, March 2012.)

However, five of the seven data team members mentioned that they felt that the process was too slow at times, especially in the beginning when they did not yet have the data:

The first phase is so elusive. You have to persist. ... The last couple of times were very meaningful, because we had the data needed to take concrete steps. During the first meeting and the ones following, I felt like we were stuck. (Interview with data team member 1, July 2012.)

This is consistent with learning new things, which in the beginning usually takes time. It is also inherent to the data team procedure where the focus lies on taking your time to really investigate the causes of a problem instead of jumping to conclusions (eg Katz, Earl, and Ben Jaafar 2009).

The data team members were asked if they were going to use the knowledge gained from participation in a data team in their own practice. Three members still saw their lack of data skills as an obstacle in the way of their starting to use data. Two members connected the knowledge gained with the knowledge they already had (as a researcher). The other two members did not connect the data team work with their own teaching practice, they indicated that a lack of time for conducting in-depth analysis would prevent them from using data in their own practice.

Still not very practical, I think right now, actually. No, I do not think so concrete. If certain things occur, we just go towards a solution, because we don't have the space or time to do such an analysis. (Interview with data team member 3, July 2012)

Resistance to change is common in education (Akmal and Miller 2003). Often, there is a tendency to immediately react instead of postponing judgement. Data use takes time, but in the long run can lead to improved education (eg Carlson, Borman, and Robinson 2011).

3.2. Effects at the learning level

3.2.1. The relevance of the conversations

The conversations in the data team addressed 'teaching, learning and materials' 36% of the time; 'supporting teaching, supporting learning and supporting materials' 55% of the time; and 'staff-issues' 9% of the time. Although the discussions in the team were relevant, initially the discussions did not focus on the way teaching and learning was organised, but on changes that other people had to make. For example, one of the data team members (2) stated at the first meeting, 'So the meaning of this is, that by means of the hypothesis we are going to investigate drop-out and come up with advice. Then, our advice can be implemented by the curriculum commission', referring to the curriculum commission's responsibility. Another team member (6) stated at the fourth meeting: 'The aim of the teacher should be that at least 90 per cent of the students complete the teaching unit'. Another team member (3) reacted: 'What motivates me is, to what extent is our teaching program the cause of drop-out?', referring to blaming the programme for the drop-out rate.

Eventually, the data team members decided to look also at the role of the teacher. However, these data were not easy accessible or available: data about progress in the course of study were available, but not about, for example, active pedagogy. The data team needs data that are fit for their purpose, and not only data assessing the easily measurable (eg Griffin et al. 2014) The data team tried to solve this issue by adapting an existing exit questionnaire to incorporate the role of the teacher. It was a time-consuming effort. However, the team did not get a high response rate (23%). At the eighth team meeting, it was stated that: 'Students indicated that they mainly blame themselves and not the teachers'. A data team member (6) reacted: 'And what did they answer to the question about active learning? Even there, eight out of nine answered that they had not been active enough in their studies, instead of blaming their teachers'.

This suggests the students have fixed traditional views about learning. The data team decided to continue only with considering students' progress in the course of study, but several of their conversations were still focused on teaching, coaching and learning in their own classrooms:

I know that in the previous year, in my own teaching unit we had four assignments and examinations. Students who complete three out four will not get their final credits for the unit. So, the more obstacles you create for accumulating the credits, the fewer credits the students get. (Data team meeting 8, member 1.)

Although many conversations started with teaching and learning, the interventions the data team developed were related to the way students learn and not to teaching. The data team members tended to attribute the problems externally instead of internally (eg Van den Hurk et al. 2014). The improvement measures were developed on a general level (extra-curricular course to develop study skills), but the teaching of the teacher educators themselves remained unchanged.

We can all try to ensure that students are studying. We and the other teachers should keep a close eye on the students: how did they complete the exams? Did everybody complete the exams? Does anyone have one postponed? As a blueprint of how quickly students know how it works. And how do they plan? (Data team meeting 10, member 4.)

The data team did not develop interventions related to teaching. Nor did they reflect on the data team method, or on the value of the method in relation to their own teaching practice, and more generally, their role in teacher training. Their learning occurred as part of their role as teachers in higher education rather than as teachers of students, as a model for students or as researchers (Livingston 2014).

3.2.2. Depth of inquiry

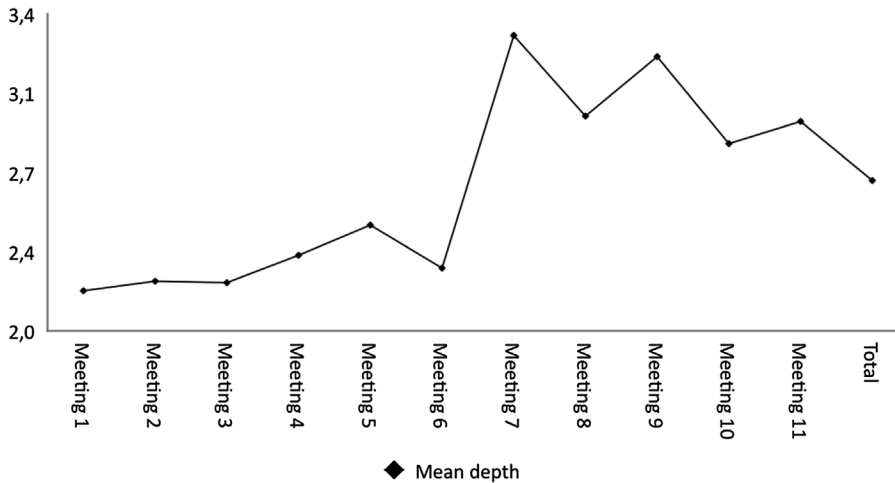
The depth of inquiry within the meetings had a recurring pattern: most of the meetings started with conversations that had no depth (no exchanges of ideas/beliefs); as the conversation progressed, the depth increased, and then decreased again. This is caused by the fact that the meetings started and ended with staff issues. For instance, meeting 4 (see Table 5; no depth 15%, some depth 58%, average depth 18% and considerable depth 0%; activities: data and quality check) started with the agenda and the minutes (the first 12 minutes: no depth). Then, based on the reactions of students who completed the exit survey as a trial, the quality of the questionnaire was discussed and the questions were adjusted. This conversation mainly had some depth (some exchange of ideas and beliefs, without fact checking), and occasionally an average depth (all members sharing ideas and beliefs, without fact checking). The meeting ended with agreements made for the next meeting (no depth). Meetings 10 and 11 were an exception to this pattern: almost the whole of both meetings had an average depth, which was due to the content of the conversations. Both meetings were about making plans for interventions to improve education based on the knowledge constructed in previous meetings.

The depth of inquiry not only varied between meetings (see Figure 1), but also increased as the data team progressed through the data team procedure. The percentage of conversations without depth was relatively high in meetings 1 and 2 (32% and 25%, respectively), which decreased to 4% and 3% in meetings 10 and 11, respectively. The depth of inquiry of the data team's conversations can be divided into three phases over time based on the overall mean depth of the meetings. Phase one (meetings 1 up to 6) was the phase in which

Table 5. The extent of depth (percentages) per meeting (M1–11).

	M1 (%)	M2 (%)	M3 (%)	M4 (%)	M5 (%)	M6 (%)	M7 (%)	M8 (%)	M9 (%)	M10 (%)	M11 (%)	Total (%)
No depth	32	25	15	17	17	17	11	2	2	4	3	12
Some depth	24	38	58	33	20	47	14	18	15	10	3	24
Average depth	38	28	18	50	63	28	8	62	43	86	94	49
High depth	6	9	9	0	0	8	67	18	40	0	0	15
Total per meeting	100	100	100	100	100	100	100	100	100	100	100	100

Note: The transcripts of all conversations were divided into parts of 10 lines. Every phrase was labelled for the extent of depth.

**Figure 1.** The overall mean depth per meeting.

Notes: The mean depth was calculated by assigning 1 to fragments of no depth, 2 to those coded as having some depth, 3 to those coded as having average depth, and 4 to those coded as having considerable depth. The overall mean depth for the meeting was based on the total value of the coded fragments for that meeting, divided by the total number of coded fragments related to depth.

the team had to be formed and the data team procedure begun, with a mean depth of 2.28. The conversations were characterised by exchanging information, for example, how to adapt the exit questionnaire. The data team members did not really focus on building knowledge because they needed to get used to each other and become familiar with the procedure.

In the second phase (meetings 7 up to 9), the conversations showed increasing depth (with a mean depth of 3.15). The data team's focus was on the data collected, the quality of the data, and the interpretations and conclusions based on data. Some of the hypotheses turned out to be wrong, which resulted in conversations with deeper levels of inquiry. New knowledge was created based on the data (eg educational background, group atmosphere and gender do not influence drop-out). New knowledge was also created based on hypotheses that the data showed to be correct, for example, with regard to a lack of study skills in the first two periods of the year influencing drop-out:

I hear too many students say: we are very busy now. In essence, that is correct, because they must now get the maximum number of credits in these periods. So, if you're talking about study ability this signal fits with the figures that we see. We can conclude, if we are talking about the allocation of credits over the year, period one is a crucial period. (Data team meeting 8, member 6.)

However, although the data team members were willing to learn and develop new knowledge based on data, when it comes to the implementation of this new knowledge, the data team members did not see this as their responsibility. This can also be seen in the third phase (meetings 10 and 11) where the mean depth of the discussions decreased a bit (to 2.88) to less than average depth. These were the meetings focused on the improvement measures, but these improvements were not related to teachers' own functioning, as illustrated by the following quote:

You should have a complete list of all the students you supervised and the credits they have accumulated so far, so you can ask every week: and where do you stand? You cannot get this information out of the system. Another prerequisite for this is, that the coach should know how the curriculum works. (Data team meeting 11, member 2.)

3.2.3. The role of data coach

With regard to the role of the coach, five of the seven data team members appreciated making decisions collectively with the support of the data coach:

Sometimes your presence was clearly felt, sometimes less clearly. You did not make the decisions, we did that together. (Interview with data team member 2, July 2012.)

Based on observations, the data coach switched between the role of coach and expert, both during the meetings and between the meetings. The coach's role for the data team depended on whether the data team needed new input (eg knowledge), or help in finding the right path. When we determined the extent to which the data coach was acting as an expert or a coach during each meeting (Figure 2), it became clear that during meetings 1, 4, 7 and 9, the data coach predominantly acted as an expert: the coach brought new knowledge about the data team method (meeting 1) and analysing data (meetings 7 and 9) into the meeting. During meetings 5, 6, 10 and 11, the data coach acted more as a coach: he modelled skills

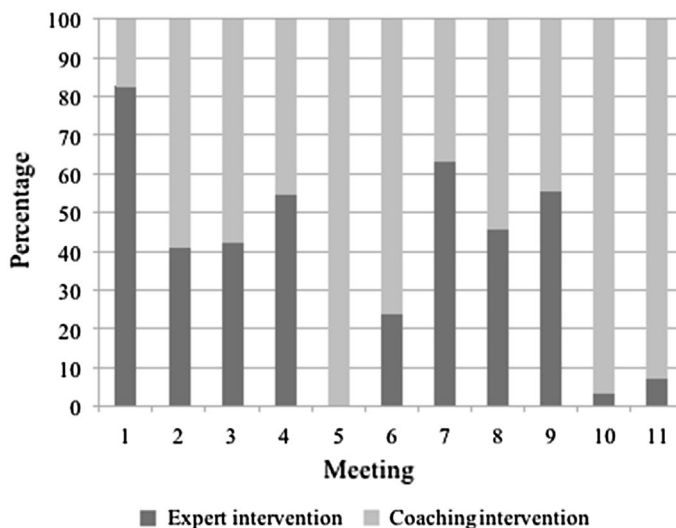


Figure 2. The percentage of expert and coach interventions per meeting.

Notes: The percentages of expert and coach interventions were calculated by labelling all fragments in which the data coach intervened as either coaching or expert interventions. The total number of fragments coded for each type of intervention per meeting was added up and divided by the total number of coded fragments related to the data coach's role for that meeting.

and assisted in collecting data (meetings 5 and 6) and in developing improvement actions (meetings 10 and 11), and during meetings 2, 3 (collecting data from the perspective of the problem and the hypotheses the data team had stated), and 8 (formulating conclusions) the data coach acted (almost) equally as an expert and as a coach. The data team members valued this balance between the roles of expert and coach:

The difference between you (data coach) as an expert and as a coach works well. We also need to learn not to rely too much on someone providing a framework. (Interview data team member 4, July 2012.)

In the expert role, the data coach explained things or the data team fell back on the knowledge/skills and/or preparation of the data coach. During the first meeting, for example, the data coach explained the data team procedure, explained the problem statement and discussed it with the data team.

In the coach role, the coach let the data team work independently, or relied on its members' content knowledge, which was crucial for the sustainability within the group. In meeting 6, the data team worked independently: the chairman was well prepared and showed adequate leadership. In meetings 10 and 11, content knowledge was crucial for developing improvement measures.

The data coach influenced the depth of inquiry. In the first three meetings of phase one, the comments that resulted in greater conversational depth came from the data coach in the role of expert (meetings 1–3: 10 fragments of the coach in an expert role and 6 fragments in a coach role). During the second half of the first phase (meetings 4–6), the data coach's comments that influenced the depth of the conversations reflected the coaching role in particular (meetings 4–6: 2 fragments in an expert role and 14 in a coach role). In the second phase, 8 of the data coach's 13 contributions, which resulted in greater conversational depth, were contributions in the role of expert. In the third phase, the data team needed no encouragement from the data coach to reach greater depth. The data coach also provided depth in the conversations by summarising conclusions, by involving other data team members in their conversations, and by asking reflective questions. For example, in data team meeting 7, the data coach asked the data team members:

Go on; help him to get all the arguments.' So another data team member responded (3): 'Another argument is that the credits have not yet been definitively entered into the system.' Whereupon another data team member (4) said: "Do not."

In the same meeting, the data coach asked data team members to summarise the previous discussion:

'What can we conclude?' A data team member (2) responded: 'More or less 70 per cent of the students have a gap between the credits they have and what they could have.' Another data team member (1) added: 'From our previous meeting we can say that almost 80 per cent of these students incur this gap in the first period.'

This enlarges the role of the data coach. This role should not only focus on teaching of the data team procedure, but should also focus on the construction of knowledge and how to promote depth of inquiry (eg Love, Stilles, Mundry, and DiRanna 2008).

4. Conclusions

This micro-process study led to detailed insights into how participation in a data team can contribute to professional development. In the conclusion section, first, answers to the

research questions are proposed. After a discussion of the findings, this section ends with implications for practice.

4.1. The research questions

4.1.1. How do members experience their participation in a data team?

With regard to the effects at the *reaction level*, we can conclude that the data team members indicated that they were, in general, positive about the data team method, and appreciated participating in the team. As several studies have shown (Borko 2004; Desimone 2009; Timperley and Earl 2012; Van Veen et al. 2010), appreciation of participating in the data team is necessary, but does not guarantee new learning (Akmal and Miller 2003).

4.1.2. What is the relevance of the conversations in the data team?

With regard to the *learning level*, the conversations that the team members had were relevant. The conversations started with a focus on the classroom, but a lack of data on teaching practices resulted in more general conversations.

4.1.3. What is the depth of inquiry of the conversations in the data team?

The effects at the learning level are also reflected in the depth of inquiry of the team's conversations. The conversations varied in depth of inquiry. Generally, within a meeting, the conversations started out with less depth (no exchanges of ideas/beliefs), increased in depth (members sharing ideas and beliefs, with or without fact checking) and decreased again. Also, across meetings, the depth of inquiry was low during the first six data team meetings, increased over time and decreased slightly during the last meetings. This could be explained by the way a group evolves (Tuckman 1965). It takes some time for a group to become effective and to reach relevance and depth in conversations (Henry 2012). Moreover, teachers need to learn not to react instantly to stimuli. This direct reaction to stimuli is what Katz, Earl, and Ben Jaafar (2009) call the activity trap: acting before thinking. This is one of the things the data team procedure aims to prevent.

Moreover, several of the hypotheses the team investigated turned out to be false (ie with regard to gender, group atmosphere and educational background). This led to increased depth of inquiry and learning. The team built new knowledge on hypotheses that turned out to be false. This is not the type of knowledge that immediately leads to changed practice, but data team members' assumptions about the problem were challenged, and the results of the data analysis undermined certain myths within the organisation. This is what Weiss (1998) calls the enlightenment function (of data). Being involved in the data team resulted in collaborative teacher learning in meaningful contexts (Voogt et al., 2011).

4.1.4. What role does the coach play in supporting the data team?

The data coach played an important role in supporting this data team (cf. Verhaeghe et al. 2011). The data coach (cf. Lachat and Smith 2005) guided the team through the procedure and maintained a focus on data and depth of inquiry. A balance between the coach role and expert role led to increased depth of inquiry in some meetings. Data team members saw the coach as a part of the team. This study shows that the data coach can steer the conversations towards greater depth by providing a role model, and by providing learners with opportunities to discuss and reflect with each other, to practise the application of new knowledge, and to

give feedback. All of these are crucial for learning, as other studies have concluded (Marsh 2012). According to Kirkpatrick's learning levels (Kirkpatrick 1960), the coach stimulates the team to get deeper in their conversations and scaffolds the data team in their learning process. Teacher learning through the data team method in this case aimed to solve a problem at the level of the Teacher Education College. We found that the teacher educators did not expand their use of data to act as a role model for their students; they did not use data to improve upon their own teaching. In general, it seems that explicit attention must be paid to the training of teacher educators with regard to applying this knowledge in the different roles they fulfil. This is in line with the complexity of professional development for teacher educators, and especially the complexity of teacher educators' identity formation (Livingston 2014).

4.2. Discussion

This exploratory study focused on the way one data team functioned at one teacher training college. By using a case study approach, the focus was on the conversations, in the data team, thus providing insights into the steps taken, the development of the conversations, and the role of the data coach. We studied opportunities for professional development of teacher educators participating in the team, focusing on the first two levels of Kirkpatrick's (Kirkpatrick 1960) evaluation model: reaction and learning (authentic learning as reflected in the conversations). Although this study was conducted in only one teacher training college, it provides us with a better reflection of teacher learning than often-used measures of perceptions of learning (eg interviews and surveys).

However, because a case study opts for analytic rather than statistical generalisation (Cohen, Manion, and Morrison 2007), the results cannot simply be transferred to other situations. This study focused on describing in depth what happened in one teacher training college where educators were learning how to use data through the data team procedure. Further research is needed in more teacher training colleges to formulate conclusions and gain more insights into the effects of data-related professional development for teacher education, as well as the factors enabling or hindering effective professional development in the use of data in the different roles teacher educators fulfil. Further research is also needed on how to generate behavioural effects and to reach organisational goals (Kirkpatrick 1960).

With regard to these higher levels of effects, the action plan that the data team developed did not incorporate their own functioning in the classroom. The intended measures were related to other teacher educators (eg curriculum commission), and to the daily teaching and coaching routine of teachers. Data team participation did not really lead to reflection on the teachers' own teaching practice. Further research can focus on how professional development of teacher educators develops in and between roles. Even when participants are satisfied with a professional development intervention, this might not lead to learning, and learning sometimes does not automatically mean that people are going to apply their new knowledge and skills, as found by several other studies (eg Alliger and Janak 1989; Alliger et al. 1997). Further research can focus on why it is so difficult to reach this behavioural level of effects, and in particular across the different roles of teacher educators.

Our study shows that a lack of measures related to the teacher's own functioning may have been (partly) caused by a lack of access and availability of data related to teaching practices, but also may have been caused by a lack of ownership over the problem. The problem is a general problem, and perhaps, in the eyes of teacher educators, not so closely

related to their own classroom teaching. A lack of ownership (eg students' results are not influenced that much by my teaching) can hinder data use (Datnow, Park, and Kennedy-Lewis 2013; Schildkamp and Kuiper 2010). Further research may focus on how these different factors can hinder or enable data-related professional development initiatives. It is important to take into account the organisational context in which data use is taking place, the characteristics of the data and the data systems available, as well as personal characteristics of the individual data users (eg ownership), as these all interact (Coburn and Turner 2012; Marsh 2012; Schildkamp and Poortman 2015).

4.3. Implications for practice

Although conceptual data use was achieved by the team, it seemed that the instrumental use of data (Weiss 1998), in which data team members actually apply their new knowledge in their own practice, was not reached. This is what Desimone (2009) calls the behavioural-level effect of professional development. Although it was not a specific focus of our study, we did notice that, with regard to the behaviour level, data team members did not make the connection between working with data in a data team and data use in their other roles. To make this transfer, we argue that explicit attention from a coach is required. The coach needs to assist not only in collecting and analysing the data, but also in linking these data to teacher educators' other roles as a model for students of their own teaching practice, and as seeking to identify appropriate measures to improve education based on data (Marsh, Sloan McCombs, and Martorell 2010). When new behaviour is the aim, the role of the data coach should also be to support teacher educators in implementing new teaching strategies (Cantrell and Hughes 2008; Neuman and Cunningham 2009). Only then can the use of data lead to improved teaching and improved student learning and achievement.

Disclosure statement

No potential conflict of interest was reported by the authors.

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