Studies in Educational Evaluation 55 (2017) 58–67

Contents lists available at ScienceDirect

Studies in Educational Evaluation

journal homepage: www.elsevier.com/locate/stueduc

Effects of a data-based decision making intervention on student achievement

L. (Laura) Staman[a,*], A.C. (Anneke) Timmermans[b], A.J. (Adrie) Visscher[a]

[a] University of Twente, The Netherlands
[b] University of Groningen, GION Education/Research, The Netherlands

ARTICLE INFO

Keywords:
Data-based decision making
Student achievement
Professional development
Intervention

ABSTRACT

Data-based decision making (DBDM) is becoming important for teachers due to increasing amounts of digital feedback on student performance. In the quasi-experimental study reported here, teachers, principals, and academic coaches from 42 schools were trained for two years in using the results of half-year interim assessments for providing students with tailor-made instruction. Our results did not show any main effects of this DBDM training trajectory on student achievement but did indicate interaction effects with students' low prior achievement levels and socioeconomic status. Teachers experience difficulties in translating student progress data into adaptive instruction in the classroom. Implications of our findings for teacher professionalization are discussed.

1. Introduction

Data-Based Decision Making (DBDM) is growing internationally. Since the 'No Child Left Behind' (2001) act was introduced in the United States American schools are expected to make decisions based on (test) data, and to meet the standards for 'Adequate Yearly Progress' (Carlson, Borman, & Robinson, 2011). Several years ago, the Dutch government developed a DBDM policy because they were concerned about the performance level of Dutch students as indicated by international comparative studies (Ministry of Education, 2007). The results of the TIMSS, PIRLS, and PISA surveys indicated, according to the Dutch government, that the performance of Dutch students was declining. The idea was that teachers and schools should make (more) use of the results from interim assessments to provide instruction matching with the, varying, instructional needs of their students (Dutch). The assumption behind this policy was that implementing DBDM could maximize the performance of all students as students were expected to be taught more in line with their needs (as indicated by the interim assessments) (Visscher, Peters, & Staman, 2010). Educators have access to an increasing amount of data.

Ikemoto and Marsh (2007) define DBDM as follows: "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). According to Dunn, Airola, Lo, and Garrison (2013) DBDM at classroom level entails "the identification of patterns of performance that unveil students' strengths and weaknesses relative to students' learning goals as well as the selection and planning of instructional strategies and interventions to facilitate student achievement of learning goals" (p. 225). This could enhance student learning if teachers reflect (more) on the impact of the instruction they have given, and attempt to provide tailor-made instruction based on their knowledge of how students perform and which learning problems they face (Schildkamp & Kuiper, 2010). Effective DBDM presupposes that teachers learn to utilize the student performance information they can retrieve from their student monitoring systems, and that they learn to choose and implement effective instructional approaches that may help improve students' mastery of subject matter content better, see Fig. 1.

However, applying DBDM effectively may be cumbersome, as previous research has shown that teachers struggle with several aspects of DBDM. Teachers struggle with utilizing test data and other data about students effectively (e.g., Marsh, Pane & Hamilton, 2006; McCaffrey & Hamilton, 2007). DBDM also presupposes that teachers master complex didactical skills, such as the differentiation of instruction in response to observed performance differences between students. The Dutch Inspectorate of Education points to the fact that teachers experience difficulties with executing these complex differentiation skills (Inspectorate of Education, 2013). Teachers need support in implementing DBDM fully (Slavin, Cheung, Holmes, Madden, & Chamberlain, 2013). We noticed that generally limited attention is paid to equipping teachers for going from data to tailor-made instruction. It was our expectation that paying attention to all DBDM components and to the prerequisites for effective DBDM might make DBDM more effective.

The University of Twente developed a training trajectory in which school teams learn to work systematically in a DBDM manner for the

* Corresponding author at: University of Twente, Faculty of BMS, Department of Teacher Development, P.O. Box 217, 7500AE Enschede, The Netherlands.
E-mail address: lstaman@rocvantwente.nl (L.L. Staman).

http://dx.doi.org/10.1016/j.stueduc.2017.07.002
Received 25 January 2017; Received in revised form 4 June 2017; Accepted 4 July 2017

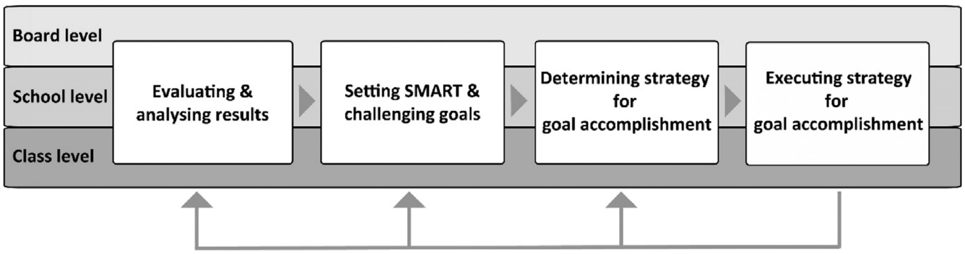

Fig. 1. Levels and components of DBDM (Keuning & Van Geel, 2012).

subject mathematics: the Focus project. In the Focus project schools were trained for working with the student test data in a wide sense: data interpretation and translating the data into tailor-made instructional strategies. The goal of the study reported here was to evaluate whether the Focus intervention that was meant to equip teachers and schools for DBDM was effective in terms of accomplishing higher levels of student achievement than a control group which was not trained for DBDM. In the following overview we first will present the results of multiple studies on the effects of DBDM interventions, and then describe our quasi-experimental study that was done to investigate the effects of the Focus DBDM intervention. In the latter we also describe how the Focus intervention was meant to equip teachers with the attitudes, knowledge and skills to adequately apply DBDM.

1.1. DBDM effects on student performance

Using student performance data (often in combination with other relevant data) to improve student performance receives much attention from scholars around the world. Various terms are used for this approach: data-driven teaching (e.g., Fullan, 2007), data-driven decision making (e.g., Wohlstetter, Datnow, & Park, 2008), and data-based decision making (e.g., Carlson et al., 2011). Despite the differing terminology, the approach is similar: to systematically work on educational improvement and basing improvement-oriented measures on student performance data. Student performance data can inform teachers about students' individual instructional needs, which can be the basis for tailor-made instruction. Data that is useful for DBDM practice includes for example the results of standardized tests, curriculum-based tests and other types of student classroom work (e.g., Lai & Schildkamp, 2013; Mandinach & Gummer, 2013).

Despite high expectations of DBDM in terms of improved student performance, scientific evidence on the effectiveness of DBDM interventions is still rather limited, meaning that current recommendations regarding the *implementation* and the *effects* of DBDM are not founded on a strong empirical basis (e.g., Hamilton et al., 2009). DBDM interventions have been evaluated in a number of (quasi-) experimental studies. Most research into the effects of DBDM reports the findings of small scale studies and non-experimental designs; we need stronger research designs. Research into the links between the DBDM components (see Fig. 1) is also scarce, or, if such studies are done, the effect of DBDM on student achievement is not investigated (Lai & Schildkamp, 2013; Marsh, 2012).

An example of one of the rare experimental studies into the effects of a DBDM intervention is the study by Carlson et al. (2011) that included coaching schools in analyzing and interpreting student performance, and the support of schools in selecting and implementing evidence-based improvement strategies. The results of this study indicated that students from schools in which student progress was analyzed using benchmark assessments performed significantly better in mathematics than a control group. The difference between both conditions proved to be 0.06 standard deviations at the student level, 0.20 at the school level, and 0.21 at the district level.

The same DBDM intervention was also investigated experimentally by Slavin et al. (2013), however, in this case not over the course of one, but four years. Both, statistically significant positive as well as statistically non-significant effects were found for reading and mathematics in grades five and grade eight. In grade five, statistically significant differences for reading and mathematics were found in the third and fourth intervention year with effect sizes varying between 0.24 and 0.50. In grade eight, positive statistically significant effects were found for mathematics and reading during the first intervention year. In the second intervention year, positive significant effects were only found for reading, and in the fourth intervention year only for mathematics. The effect sizes varied between 0.17 and 0.31. An important finding is that the largest effects were found after four intervention years. According to Slavin et al. (2013), schools started to change and improve instruction only after the third intervention year. The first two years of the intervention mainly included the analysis and interpretation of available data; "…first and second year interventions were analogous to taking a patients temperature, not providing a treatment" (Slavin et al., 2013, p. 390). Duration is an important characteristic of effective professional development, because learning and changing practice takes time. Changing teacher behavior is not easy, because of the many obligations face in their work (Van Veen, Zwart, & Meirink, 2010). In the view of Supovitz and Turner (2000) it takes eighty hours to change teacher behavior, according to Timperley (2008) it takes one to two.

Ledoux, Blok, Bogaard, and Krüger (2009) stated that Dutch research into DBDM and its effects on student performance is still limited. An example of a Dutch study into DBDM is the study by Van Kuijk (2014). An effect of 0.37 for reading comprehension was reported in a study using a matched-pairs design (Van Kuijk, 2014), whereas the same intervention did not lead to statistically significant effects on students'mathematics performance (Ritzema, 2015). In both projects, teachers were trained in formulating standards and performance goals for each student as well as in utilizing data and learning how to apply modelling for reading and mathematics instruction.

Faber and Visscher (2014) conducted a meta-analysis to summarize the results of experimental studies on the use of digital student monitoring systems, an important DBDM component (Visscher et al., 2010), on student performance. An average effect size of 0.38 was found for interventions aimed at the use of digital student monitoring systems with small groups of children. For the implementation of digital student monitoring systems in larger contexts (school-wide, or school board-wide) a positive, but smaller effect was found (effect size 0.06). Factors that proved to promote the intended effects of digital student monitoring systems on student performance are a high feedback frequency, and the use of monitoring systems that include instructional advice in their feedback to practitioners. Finally, interventions involving system implementation activities (e.g., training teachers for system use) at least once a month proved to be more effective.

Overall, the results of the studies presented here show a mixed picture of the effects of DBDM on students' (mathematics) performance. In some studies, the DBDM intervention effects are significant, whereas in others they are not. Also, the significant effects' magnitude varies considerably. These discrepant findings may be due to differences in the feedback that teachers receive in terms of frequency and content (e.g., with, or without follow-up advice). Differences between DBDM interventions are also important, e.g., how and how much users are trained in system use in the broad sense of the term: learning to use data to provide instruction in line with observed student needs.