Article

HAMMILL INSTITUTE ON DISABILITIES

Assessment for Effective Intervention
2021, Vol. 46(4) 247–258

DOI: 10.1177/1534508420902523
aei.sagepub.com
SAGE

Does Training Predict Second-Grade Teachers' Use of Student Data for Decision-Making in Reading and Mathematics?

Marissa J. Filderman, MEd[1], Jessica R. Toste, PhD[1], and North Cooc, PhD[1]

Abstract

Although national legislation and policy call for the use of student assessment data to support instruction, evidence suggests that teachers lack the knowledge and skills required to effectively use data. Previous studies have demonstrated the potential of training for increasing immediate teacher outcomes (i.e., knowledge, skills, and beliefs), yet research is still needed that investigates whether these immediate learning outcomes correspond to improved practices in reading and math instruction. Using the Early Childhood Longitudinal Survey: Kindergarten (2011), the present study sought to investigate whether data-focused training predicted teacher use of data for four prevalent decision-making outcomes: monitor progress on specific skills, identify skill deficits, monitor overall progress of students performing below benchmark, and determine placement in instructional tiers. Results indicate that professional development to use data to identify struggling learners and coursework focused on the use of assessment to select interventions and supports significantly predicted teachers' frequent use of data across key decision-making dimensions in reading instruction. Results for math instruction differ in that more frequent data use was not consistent across outcomes, more training sessions were needed, and professional development to use data to guide instruction significantly predicted use of data to monitor students who performed below benchmark.

Keywords

data use, response to intervention, teacher training, professional development

Federal educational policy and legislation (Civic Impulse, 2017; Every Student Succeeds Act, 2015; Individuals with Disabilities Education Improvement Act [IDEA], 2004) call for use of student assessment data to improve instruction. These data are to be used in various ways along a spectrum of student needs, from monitoring student progress in the general education setting to determine efficacy of instruction, to identifying students who may be at risk and in need of additional intervention, to intensifying intervention for students who struggle the most through special education services. Although schools have been collecting increasing amounts of data, teachers report and have been observed to lack key understandings necessary to interpret and use data for these varied purposes (Gallagher et al., 2008; Means et al., 2011). In turn, researchers and teacher educators have noted a concerning lack of data use to inform classroom instruction (Datnow & Hubbard, 2016; Mandinach & Gummer, 2016).

In recent years, there has been an increasing call to support teachers in building the data literacy skills needed to use data effectively (Hoogland et al., 2016; Lai & McNaughton, 2016; Mandinach & Gummer, 2016). A recent meta-analysis reviewed 33 studies that provided teachers with data literacy training, with findings indicating strong positive outcomes on teacher knowledge, skills, and beliefs surrounding data (Authors, 2019). However, the authors noted that despite these promising findings, whether these immediate outcomes translate into practice remains to be investigated. Understanding factors that predict teachers' use of student data in practice is critical to improving instruction. As such, the purpose of the present study was to investigate whether training in the use of data corresponds with increased data use by teachers using a nationally representative data set. Specifically, using the nationally representative Early Childhood Longitudinal Survey: Kindergarten (ECLS-K: 2011) data set, this study explores whether training provided

[1]The University of Texas at Austin, TX, USA

Corresponding Author:
Marissa J. Filderman, Department of Special Education, The Meadows Center for Preventing Educational Risk, The University of Texas at Austin, 1 University Station, D5300, Austin, TX 78712, USA.
Email: marissa.filderman@utexas.edu

to general education teachers (i.e., professional development [PD] to use data to identify struggling learners; PD to use data to guide instruction; coursework on the use of data to select interventions and supports for students) predicts increased self-reported data use for four distinct purposes (i.e., monitor students' progress on specific skills over the school year; identify deficits in specific skills of struggling students; monitor the progress of students who fall below benchmark levels; and determine whether students need placement in a more or less intensive level of instruction). Findings from this study will provide insight into the impact of data-focused training on the use of data in practice, and reveal remaining areas in which teachers may require continued support.

Uses for Data in Education

The reauthorization of the IDEA (2004) emphasized the use of data to identify and support students with disabilities through a response to intervention (RTI) framework. The RTI framework requires increased use of data at each of three tiers of instructional intensity in core content areas and, correspondingly, more in-depth teacher expertise at each level. As such, some of the primary uses for student data are to: (a) monitor each student's progress on specific skills, (b) identify skill deficits, (c) monitor progress more frequently for students who fall below benchmark, and (d) determine student intervention response. The outcomes in the present study align with these four purposes of data use.

Teachers in both general and special education are expected to collect and evaluate data to improve and target instruction through the RTI process (Civic Impulse, 2017; Council of Chief State School Officers, 2012; Mandinach & Gummer, 2016). In Tier 1, teachers implement evidence-based classroom curriculum to the whole group. During this stage, teachers are expected to monitor the progress of each student on specific skills to determine what students may be at-risk for failure (i.e., are not meeting benchmark levels of growth; Fuchs et al., 2012; Supovitz & Klein, 2003), what skills need to be re-taught (Supovitz & Klein, 2003), grouping of students for instruction (Hoover & Abrams, 2013), and overall efficacy of instruction (Hoover & Abrams, 2013). When students are identified as being at-risk for failure, they are moved to Tier 2, or supplemental intervention delivered in small groups, and then Tier 3, or intensive intervention delivered to one to three students with persistent learning difficulties or disabilities (Fuchs et al., 2012).

As students receive increasingly intensive instruction along these tiers, teachers are expected to monitor progress more frequently for the overall purpose of identifying student response to intervention—that is, to decide whether a student needs more or less intensive intervention. To further target student needs, teachers use data to identify skill deficits, choose an aligned intervention based on those skill deficits, and monitor progress on those specific skills to determine any necessary adjustments to the intervention (Balu et al., 2015). Due to the breadth of knowledge and skills required to support data use, many teachers report that they need additional training to use data effectively (Datnow & Hubbard, 2016; Means et al., 2011; Wayman & Jimerson, 2014). Reflective of this need, research has also called for improved teacher training in data use (Mandinach & Gummer, 2016).

Teacher Training in Data Literacy

To successfully use data, teachers need to be able to collect, comprehend, and interpret the implications of data—a skillset known broadly as data literacy (Mandinach & Gummer, 2016). Each of these primary skills requires a great deal of nuanced understanding in order to effectively use data in the classroom. For instance, data collection requires teachers to identify skills to target; select an appropriate tool to monitor growth on those skills; understand psychometric properties of the selected tool; and access multiple databases with student information. Data comprehension requires teachers to understand how to graph data; interpret the graphs; understand rules for when change to intervention would be warranted; and understand multiple conflicting sources of information. Finally, interpreting the data requires teachers to understand what changes to make to better align instruction with student needs, and how to base changes on theories of reading and math development. Observational studies of teachers have demonstrated that many teachers struggle to understand and use data, including locating and articulating the key information from progress monitoring graphs, understanding the slope, making instructional changes based on data, and using data systematically to make these changes (Espin et al., 2017; van den Bosch et al., 2017; Wagner et al., 2017). Based on the array of understandings required to use data effectively, and observed challenges many teachers face with data use, it is no surprise that many teachers report the need for additional training to use data effectively (Means et al., 2011).

It has been generally posited that teacher knowledge, skills, and beliefs can be improved through training (Desimone, 2009; Guskey, 2002). This theory was supported with a recent meta-analysis on data literacy training, which found training to have significant, positive effects on teacher data use (Filderman et al., 2019). Outcomes of training can be further enhanced by providing teachers with high-quality training, with key components including content-focus, or relevance to student needs; interactivity, or opportunities for teachers to engage in content; coherence, or alignment with teachers' beliefs; duration, or taking place over an amount of time that allows for teacher learning of content; and collaboration, or opportunities to work through applications with peers (Desimone, 2009). A wide range of training quality was reported in the aforementioned meta-analysis; for instance, trainings varied by the content included (i.e., one to three data literacy skills were targeted), duration, and collaborative opportunities provided. This information is key in understanding what kind of training is being provided to teachers, and how the qualities of these trainings may impact teacher learning.

Importantly, several critical limitations were noted by the authors of this study, including the lack of application measures—that is, measures of direct application of the skills learned—as well as a lack of delayed posttest measures to determine whether teacher training translated into long-term increased use of data. The few studies that did include such measures are promising; for instance, studies that used instructional plan sheets to measure teacher application of skills learned found that teachers who received training used data to inform instruction significantly more than colleagues who did not receive such training (Fuchs et al., 1989, 1994). Despite these findings, the long-term applications and implications of data literacy training remain mostly unexplored; therefore, the present study sought to investigate whether training in data literacy was predictive of increased use of data in the classroom.

Purpose of the Present Study

Previous studies have indicated that training in data literacy increases immediate knowledge and skills of teachers related to data use; however, it has yet to be determined whether receiving such training leads to actual use of data in the classroom. To address this question, we utilized unique data from the restricted version of the ECLS-K: 2011. This nationally representative data set provides self-report data from a large sample of teachers from a variety of school settings. Using these data, we sought to establish a preliminary link between data literacy training and data use practices. Specifically, the research question guiding this study is to what extent does data-focused training predict teacher use of data for four decision-making purposes (i.e., using data to monitor progress on specific skills, to identify skill deficits, to monitor the progress of students performing below benchmark, and to determine placement in instructional tiers)?

Method

Data Source

The data for this study come from the ECLS-K: 2011, a nationally representative, longitudinal study conducted by the National Center for Education Statistics (NCES). The survey follows approximately 18,000 students from 970 schools from kindergarten through fifth grade, with data gathered in the fall and spring of each year. At each time point, students are directly assessed and adults—such as teachers, parents, and before/after school caregivers—are surveyed. The aim of the survey overall is to determine how children develop and what factors influence their development as relates to education (Tourangeau et al., 2015).

The primary purpose of the teacher questionnaire was to gauge students' classroom experiences and how they relate to their overall development (Tourangeau et al., 2015). The questions are split into two assessments: teacher-level and child-level questions. Teacher-level questions were designed to assess the classroom atmosphere to which students were exposed, and included items such as PD and practices. Child-level questions were designed to assess the child's experiences in the classroom directly and included items such as the number of struggling readers in the classroom and the child's behavior in the classroom. In the present study, we utilize data collected from the general classroom teacher questionnaire, which is administered to all teachers of the students included in the study.

Sample

The current sample is drawn from data collected from second-grade general education teachers surveyed in the spring of 2013, which was the first time teachers were asked to answer questions related to their use of data. Cases with full data were retained, and then duplicates were removed for students with the same teacher so that each teacher's response was counted only once. The final available sample of teachers interviewed in the spring of 2013 included approximately 5,330 teachers. The mean years of experience for teachers included in the survey was 14.69 years ($SE = 0.14$), with a range of 0 to 50 years of teaching experience. The highest degree obtained for 50% of teachers ($n = 2,370$) was a bachelor's degree and for 47% was a master's degree ($n = 2,240$). Certifications for sampled teachers included elementary (43%, $n = 2,000$), special (6%, $n = 280$), early elementary (24%, $n = 1,130$), and English as a Second Language (26%, $n = 1,230$). Sampled teachers were predominantly White (85%; $n = 4,060$), followed by Hispanic (12%; $n = 570$), Black (7%; $n = 330$), Asian (2%; $n = 110$), and other (e.g., American Indian/Alaskan Native, Hawaiian/Pacific Islander; 1%; $n = 70$). Sampled teachers were predominantly female (94%; $n = 4,400$) and were on average 47 years old ($SE = 11.5$).

Measures

The ECLS-K:2011 includes questions directly related to teachers' data collection and use (see Supplemental Table S1), which were the key outcome variables in the present study. The independent variable was training in the use of data for math and reading. Covariates were also included to control for potential confounding factors. Each of these factors are explained in the following.

Teacher reports of data use. Participating teachers reported on their frequency of data use, separately for reading and math, for the following purposes: (a) *progress monitoring*, to monitor each student's progress on specific skills over the school year; (b) *deficit*, to identify the deficits in specific skills of struggling students; (c) *benchmark*, to monitor the progress of students who fall below benchmark levels; and (d) *placement*, to determine whether students need placement in a more or less intensive level of instruction (see Table S1).

The outcomes were considered separately because each use for data represented different, albeit related, constructs; therefore, considering each separately presented the opportunity for more nuanced exploration of how data training is related to data use for various purposes. For instance, identifying the specific skills students are struggling with implies an approach to data that entails error analysis to diagnose areas of struggle to target for instruction. Monitoring the progress of students below benchmark does not imply this step of identifying specific skill deficits, but rather entails determining whether students are making adequate progress according to the data which is another type of decision-making altogether. Finally, determining whether students require more or less intensive intervention is a hallmark of the RTI process, whereby teachers determine not only whether students are making adequate progress, but what this means for the level of intensity of instruction they receive. Exploring how training impacts these unique uses for data thus had important implications for beginning to understand the gaps in knowledge and skills that remain after data-focused training.

The original 7-point scale of the outcome variables was *never, once a year, two times a year, three to four times a year, five to eight times a year, one to two times a month*, and *one to two times a week*. Each outcome was dichotomized into frequent and infrequent use of data for decision-making purposes for several reasons. First, the responses for this variable were skewed, such that few respondents answered on the lower end of possible responses (e.g., range from $M = 5.09$, $SD = 1.68$ to $M = 5.78$, $SD = 1.29$ across outcomes). Second, we operationalized frequency of data use based on guidelines for the frequency with which data should be evaluated for decision-making purposes (see Ardoin et al., 2013 for a synthesis of the evidence). Thus, frequent use of data included *one to two times per month* and *one to two times per week*.

Training in data use. We utilized three variables related to training, which were asked separately for reading and math (see Table S2). The two types of PD considered were (a) PD to use data to identify struggling learners and (b) PD to use data to guide reading and math instruction. The scale for these variables ranged from *never, once, two times, three to four times, and more than four times*. These scales were kept in their original form as 5-point scales, as the amount of PD received may impact its efficacy and long-term impacts. *Assessment course* asked whether the teacher had taken a college course related to the use of formal assessment data to inform their choice of reading or math interventions and supports for students.

Covariates. Student characteristics considered included the proportion of students performing below grade level, as classes with more lower performing students may have higher teacher reports of data use (Balu et al., 2015); the proportion of male students in the class, as males tend to have more reported difficulties with learning (Share & Silva, 2003); the proportion of non-White students, as students of color tend to be referred for more intensive instruction (Zhang et al., 2014); the proportion of students who were English Learners (ELs), as ELs also tend to struggle with learning (Abedi & Gándara, 2006); and the proportion of students with a disability (SWD), as again this might be associated with increased data use.

The proportion of struggling readers was divided into percentiles, with below 25th percentile representing the lowest proportion of struggling readers in the classroom based on the reading assessment administered as part of the survey, and 75th to 100th percentile representing the greatest proportion of struggling readers in the classroom. The proportion of males, ELs, and SWDs were reported as raw numbers and converted into a proportion by dividing by the number of students in the class. The proportion of non-White students was calculated by subtracting the White students from the total number, and dividing the remainder by the total number of students in the classroom to create a proportion.

Teacher characteristics included years of experience, education level, certification type, and self-efficacy. Experience and education level were included as it is plausible that teachers with more experience and education would be more knowledgeable, which could influence frequency of data use (e.g., Spear-Swerling & Cheesman, 2012). Alternatively, teachers with less experience may also use data more frequently as they tend to be more open to new instructional methods (e.g., Boardman et al., 2005). Certification was included as a covariate because there is reason to believe certain certification types (e.g., special education) may have increased emphasis on data use as part of their training program (e.g., for assessment of students with disabilities; Mandinach & Gummer, 2016). Finally, self-efficacy was included as a covariate because teachers' belief in their ability to impact change in their students' performance has been found to impact teacher use of data (Ingram et al., 2004; Schildkamp & Kuiper, 2010). A combination of questions were included for this covariate, including: (a) "By trying a different teaching method, I can significantly affect a student's achievement," (b) "If some students in my class are not doing well, I feel that I should change my approach to the subject," and (c) "If I try really hard, I can get through even to the most difficult or unmotivated students."

School characteristics included as covariates were the availability of support staff, which included staff who engaged in collection, organization, and management of assessment data; staff to support in the interpretation and use of data to guide instruction; and the presence of a reading or math specialist. Each of these staff members have been found to support school use of the RTI process (e.g., Balu et al., 2015). In addition, the Title 1 status of the school was controlled for as an indicator of school socioeconomic status.

Complex survey design. To account for the complex survey design and ensure inferences were nationally representative, the following sampling weights, primary sampling unit, and strata were used: W6CS6P_2T0, W6CS6P_2TPSU, and W6CS6P_2TSTR. Importantly, the ECLS-K:2011 focuses on student-level data; therefore, teachers are weighted according to the student sample.

Analytic Method

To analyze the research questions, we used logistic regression to predict data use among teachers. We fit the following model:

$$\mathrm{logit}(p) = \beta PD + \alpha X_j + \tau W_j + \lambda Z_j + \theta_s,$$

where p = the probability of the data use outcome, β = the type of PD provided, X is a vector of controls for teacher characteristics, W is a vector of controls for student characteristics at the classroom level, and Z is a vector of controls for school characteristics. Covariates were included on the teacher, student, and school level, creating one unadjusted model and four adjusted models for each outcome considered. Models were fitted for each of the four frequent data use outcomes considered: (a) progress monitoring, (b) deficit, (c) benchmark, and (d) placement.

Results

Descriptive statistics for each of the predictors are presented in Table 1. Three types of training were considered: PD to use data to identify struggling learners, PD to use data to guide instruction, and college coursework related to the use of formal assessment data for reading and math. The odds of these trainings on frequent progress monitoring for data use outcomes, along with models that include teacher, student, and school covariates, are presented in Tables 2 through 5. Results will be reported by data use outcome variables: (a) progress monitoring, (b) deficit, (c) benchmark, and (d) placement.

Progress Monitoring

The first outcome considered was the use of data to monitor each student's progress on specific skills over the school year. Model 1 in Table 2 shows descriptive trends indicating that, for reading instruction, teachers who received more training focused on the use of data to identify struggling learners tended to also report greater use of progress monitoring. In particular, teachers who attended training on identifying struggling learners more than four times had 1.91 times the odds of using progressing monitoring than teachers who did not attend at all. The result remains similar when controlling for covariates at each level. When controlling for teacher, student and school characteristics in Models 2 to 5, the results also show attending an assessment course is associated with higher odds of using progress monitoring (odds ratio [OR] = 1.24–1.36, $p < .05$). The final model with all covariates shows that training in identifying struggling learners and assessment coursework are related to greater use of progress monitoring. The bottom panel of Table 2 presents results for math instruction. The results are different as only attending an assessment course is related to using progress monitoring when teaching math when controlling for covariates.

Deficit

The second outcome considered using data to identify the deficits in specific skills of struggling students. Models 1 and 2 in Table 3 show descriptive trends indicating that for reading and math instruction, teachers who received more training focused on the use of data to identify struggling learners tended to also report greater use of progress monitoring. In particular, for reading instruction teachers who attended training on identifying struggling learners more than four times had 1.81 times the odds, while for math instruction teachers had 2.17 times the odds of using progressing monitoring frequently than teachers who did not attend at all. When controlling for student and school characteristics, as well as in the full model, results are slightly different for reading instruction in that receiving training more than four times was no longer significant; however, training remained significant when provided three to four times. The results also show across all models that attending an assessment course was associated with higher odds of using progress monitoring (OR = 1.34–1.45, $p < .01$ for reading; OR = 1.41–1.48, $p < .001$ for math).

Benchmark

The third outcome considered using data to monitor the progress of students who fall below benchmark levels. Each of the models reported in Table 4 demonstrate trends

Table 1. Descriptive Statistics.

Variable	Reading M (SD)	Reading n	Math M (SD)	Math n	Combined M (SD)	Combined n
Progress[a]	0.57 (0.49)	4,600	0.65 (0.48)	4,570		
Deficit[a]	0.65 (0.48)	4,590	0.69 (0.46)	4,570		
Benchmark[a]	0.68 (0.47)	4,590	0.66 (0.47)	4,560		
Placement[a]	0.51 (0.50)	4,590	0.53 (0.50)	4,540		
Data identify[b]	1.90 (1.36)	4,360	1.56 (1.37)	4,350		
Data guide[b]	1.88 (1.37)	4,350	1.53 (1.37)	4,320		
Assessment course[b]	0.68 (0.47)	4,580	0.52 (0.50)	4,580		
Years experience					14.69 (9.58)	4,720
Elementary certification					0.92 (0.27)	4,660
Special education certification					0.11 (0.31)	4,650
Early childhood certification					0.34 (0.47)	4,650
ESL certification					0.27 (0.44)	4,650
Education level[c]					0.50 (0.50)	4,720
Staff assessment[d]					0.50 (0.50)	5,330
Staff interpretation[d]					0.53 (0.50)	5,330
Specialist[c]	0.64 (0.48)	4,670	0.26 (0.44)	4,680		
Title 1					1.28 (0.45)	4,300
Below level[e]	2.49 (1.11)	4,470	2.48 (1.13)	4,410		
Non-White[f]					0.94 (0.26)	4,440
Male[f]					0.52 (0.10)	4,620
Disability[f]					0.12 (0.17)	4,550
EL[f]					0.07 (0.04)	4,600

Source. U.S. Department of Education, *Early Childhood Longitudinal Study, Kindergarten Class of 2010-11* (*ECLS-K:2011*), *Restricted Dataset.*
Note. Numbers of teachers reported are those that answered each question; teachers typically taught both math and reading. ESL = English as a Second Language; EL = English Learner.
[a]Scale 0 = *Infrequently* (less than one per month), 1 = *Frequently* (one or more per month). [b]Scale 0 = *none*, 1 = *one session*, 2 = *two sessions*, 3 = *three to four sessions*, 4 = *more than four sessions*. [c]0 = *Bachelors*, 1 = *Master's or higher*. [d]Scale 0 = *resource not available*, 1 = *resource available*. [e]Scale 1 = *0% to 24.9%*, 2 = *25% to 49.9%*, 3 = *50% to 74.9%*, 4 = *75% to 100%*. [f]Scale 0 = *not present*, 1 = *present*.

that, for reading instruction, teachers who received training focused on the use of data to identify struggling learners tended to also report greater use of progress monitoring, with odds generally increasing as teachers received more training. For example, Model 5 indicates that, when controlling for student, teacher, and school characteristics, teachers who attended such training more than four times had 2.19 times the odds of using progressing monitoring than teachers who did not attend at all. For reading instruction, taking an assessment course also significantly predicted teachers' reported data use in each model (OR = 1.27–1.46, $p < .05$). These results are different when considering data use for math instruction. Models 1 and 2 indicate that receiving training to identify struggling learners was significantly associated with higher odds of reporting frequent data use; however, this trend does not continue when controlling for student or school characteristics. Training in using data to guide instruction was shown to be associated with increased odds of reported use of progress monitoring, with more training associated with higher odds. Specifically, with a full set of controls in Model 5, teachers had 1.73 times the odds of using progress monitoring than teachers who did not receive this training. Assessment courses were again shown to be a significant predictor of data use for math instruction (OR = 1.36–1.43, $p < .01$).

Placement

The fourth outcome considered using data to determine whether students need placement in a more or less intensive level of instruction. For reading instruction, each of the models reported in Table 5 show that training focused on the use of data to identify struggling learners was associated with greater use of progress monitoring regardless of the amount of training received, with odds again increasing as teachers received more training. Teachers were much more likely to report using progress monitoring data for placement of students when they received this training; for example, Model 1 in Table 5 shows that teachers who attended training on identifying struggling learners more than four times had 3.01 times the odds of using progressing monitoring than teachers who did not attend at all. For math instruction, teachers were also more likely to report using progress

Table 2. Odds Ratios for Progress Monitoring Outcome.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Reading	n = 3,670	n = 3,520	n = 3,370	n = 3,160	n = 2,830
DI: One	1.27 (.20)	1.27 (.21)	1.33 (.20)	1.42 (.25)	1.49 (.25)*
DI: Two	1.38 (.22)*	1.38 (.21)*	1.45 (.23)*	1.44 (.25)*	1.47 (.25)*
DI: Three to four	1.39 (.25)	1.38 (.23)	1.40 (.26)	1.38 (.27)	1.38 (.27)
DI: More than four	1.91 (.45)**	1.88 (.43)**	1.94 (.48)**	1.71 (.42)*	1.76 (.45)*
DG: One	1.27 (.17)	1.26 (.17)	1.16 (.17)	1.25 (.19)	1.07 (.19)
DG: Two	1.12 (.15)	1.12 (.15)	1.13 (.16)	1.12 (.17)	1.09 (.18)
DG: Three to four	1.13 (.18)	1.14 (.18)	1.08 (.21)	1.22 (.22)	1.08 (.21)
DG: More than four	1.19 (.24)	1.15 (.22)	1.12 (.24)	1.21 (.26)	1.02 (.22)
Assessment course	1.25 (.12)	1.24 (.12)*	1.25 (.12)*	1.36 (.14)**	1.32 (.14)*
Math	n = 3,630	n = 3,490	n = 3,300	n = 3,130	n = 2,770
DI: One	1.02 (.15)	1.01 (.16)	1.04 (.16)	1.02 (.16)	0.99 (.18)
DI: Two	1.07 (.19)	1.08 (.20)	1.08 (.20)	1.13 (.21)	1.10 (.23)
DI: Three to four	1.39 (.34)	1.41 (.34)	1.48 (.40)	1.41 (.36)	1.44 (.39)
DI: More than four	1.66 (.54)	1.95 (.65)*	1.66 (.58)	1.49 (.55)	1.61 (.63)
DG: One	1.18 (.19)*	1.16 (.18)	1.12 (.18)	1.27 (.22)	1.21 (.21)
DG: Two	1.14 (.19)	1.08 (.18)	1.07 (.19)	1.10 (.19)	1.00 (.19)
DG: Three to four	0.96 (.21)	0.95 (.20)	0.93 (.23)	1.07 (.23)	1.02 (.25)
DG: More than four	1.27 (.35)	1.07 (.31)	1.21 (.35)	1.35 (.41)	1.10 (.36)
Assessment course	1.31 (.12)**	1.32 (.12)**	1.33 (.13)**	1.26 (.12)*	1.25 (.13)*

Source. U.S. Department of Education, *Early Childhood Longitudinal Study, Kindergarten Class of 2010-11* (*ECLS-K:2011*), *Restricted Dataset.*
Note. Scale 0 = *Never*, 1 = *Once*, 2 = *two times*, 3 = *three to four times*, 4 = *more than four times; reference group* = 0. Model 2: teacher covariates include self-efficacy, years of experience, certification type, and highest education level obtained; Model 3: student covariates include race, disability status, English Learner status, gender, and risk status for reading or math; Model 4: school covariates include availability of support staff and Title 1 status; Model 5 is a fully conditional model that controls for all student, teacher, and school covariates. Not all teachers responded to each item, leading to different numbers of respondents for each model. DI = PD to use data to identify skill deficits; DG = PD to use data to guide instruction; PD = professional development.
*$p < .05$. **$p < .01$. ***$p < .001$.

monitoring when they received training to identify struggling learners, but only when the received more than four trainings across all models (OR = 1.82–2.23, $p < .05$). Odds of using data were significantly related to taking an assessment course in Models 1, 3, 4, and 5 for reading (OR = 1.21–1.28, $p < .05$), and across all outcomes for math (OR = 1.39–1.49, $p < .001$).

Discussion

The purpose of this study was to determine whether training in data literacy predicted increased teacher use of data as measured by self-reports of data use across four distinct outcomes: monitoring progress on specific skills, identifying the deficits in specific skills of struggling students, monitoring the progress of students who fall below benchmark levels, and determining whether students need placement in a more or less intensive level of instruction.

Effects of Training on Teacher Use of Data

Overall, results of this study indicate that training predicted increased teacher reports of their use of data for various outcomes. The finding that PD and coursework were associated with reports of more frequent data use is supported by a widely accepted conceptual framework grounded in theory of teacher change and instruction that posits that training influences teacher knowledge, skills, and beliefs, which in turn influences teacher practice and, ultimately, student outcomes (Desimone, 2009). As research has previously suggested that training improves immediate teacher outcomes, yet there is not a wealth of research on whether this training then improves practice (e.g., Authors, 2019), this is a promising finding. However, there were differences in this finding based on the type and intensity of training that teachers received, as well as the type of instruction being delivered, pertaining to several data use outcomes. As a result of exploring the data use outcomes separately, these differential findings expose important gaps between training and practice.

Type and intensity of training. PD that focused on the use of data to identify struggling students was shown to be associated with more frequent data use for all purposes considered for teaching reading, and for identifying skill deficits and determining placement in levels of intervention intensity for teaching math. Across these outcomes, more training sessions were associated

Table 3. Odds Ratios for Deficit Outcome.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Reading	*n* = 3,660	*n* = 3,520	*n* = 3,370	*n* = 3,160	*n* = 2,830
DI: One	1.34 (.24)	1.34 (.24)	1.36 (.24)	1.37 (.27)	1.39 (.27)
DI: Two	1.46 (.27)*	1.48 (.27)**	1.50 (.28)*	1.39 (.27)	1.48 (.31)
DI: Three to four	1.73 (.33)**	1.76 (.33)**	1.67 (.34)*	1.55 (.30)*	1.62 (.33)*
DI: More than four	1.81 (.49)*	1.87 (.48)**	1.68 (.47)	1.60 (.46)	1.62 (.48)
DG: One	1.19 (.17)	1.21 (.17)	1.13 (.16)	1.22 (.22)	1.14 (.22)
DG: Two	1.20 (.20)	1.19 (.20)	1.24 (.21)	1.22 (.23)	1.19 (.24)
DG: Three to four	1.03 (.20)	1.01 (.19)	1.01 (.21)	1.12 (.25)	1.01 (.23)
DG: More than four	1.30 (.29)	1.23 (.25)	1.33 (.31)	1.24 (.31)	1.13 (.28)
Assessment course	1.34 (.12)**	1.34 (.12)**	1.34 (.13)**	1.44 (.14)***	1.45 (.16)**
Math	*n* = 3,620	*n* = 3,480	*n* = 3,290	*n* = 3,130	*n* = 2,770
DI: One	1.20 (.15)	1.28 (.17)	1.18 (.16)	1.23 (.17)	1.23 (.20)
DI: Two	1.22 (.23)	1.27 (.24)	1.21 (.22)	1.38 (.29)	1.46 (.30)
DI: Three to four	1.76 (.37)**	1.77 (.37)**	1.76 (.38)**	1.83 (.42)*	1.79 (.40)*
DI: More than four	2.17 (.73)*	2.49 (.85)**	2.14 (.74)*	2.11 (.81)	2.26 (.87)*
DG: One	1.16 (.16)	1.15 (.17)	1.14 (.18)	1.16 (.19)	1.14 (.21)
DG: Two	1.14 (.21)	1.09 (.20)	1.10 (.21)	1.00 (.20)	0.91 (.19)
DG: Three to four	0.99 (.20)	1.02 (.21)	0.95 (.22)	1.008 (.21)	1.09 (.24)
DG: More than four	1.50 (.45)	1.29 (.38)	1.47 (.47)	1.45 (.48)	1.24 (.42)
Assessment course	1.44 (.13)***	1.48 (.14)***	1.44 (.14)***	1.41 (.13)***	1.41 (.13)***

Source. U.S. Department of Education, *Early Childhood Longitudinal Study, Kindergarten Class of 2010-11* (*ECLS-K:2011*), *Restricted Dataset.*
Note. Scale 0 = *Never*, 1 = *Once*, 2 = *two times*, 3 = *three to four times*, 4 = *more than four times; reference group* = 0. Model 2: teacher covariates include self-efficacy, years of experience, certification type, and highest education level obtained; Model 3: student covariates include race, disability status, English Learner status, gender, and risk status for reading or math; Model 4: school covariates include availability of support staff and Title 1 status; Model 5 is a fully conditional model that controls for all student, teacher, and school covariates. Not all teachers responded to each item, leading to different numbers of respondents for each model. DI = PD to use data to identify skill deficits; DG = PD to use data to guide instruction; PD = professional development.
*$p < .05$. **$p < .01$. ***$p < .001$.

with higher likelihood of teachers using data. Consistent with the literature, this suggests that more intensive training leads to increased teacher outcomes (Darling-Hammond et al., 2009; Desimone, 2009; Guskey & Yoon, 2009). It is, however, important to note that teachers who received as little as one session of training were significantly more likely to report frequent data use for using data to monitor the progress of students below benchmark in reading, and for using data to determine placement in more or less intensive levels of intervention in reading. This seems to suggest that, at least for some data use outcomes, teachers may require a less intensive training on this particular topic to use data more frequently, which stands in contrast to existing literature (Darling-Hammond et al., 2009; Desimone, 2009; Guskey & Yoon, 2009). This suggests that brief, targeted training in the use of data to identify struggling readers may impact teacher use of data, which would make training teachers highly feasible.

PD that focused on using data to guide instruction only significantly predicted teachers' frequent use of data for monitoring students below benchmark in math. This is potentially problematic as, to use data effectively for the purposes explored in this study, teachers need to use data not only to identify students, but to guide their instruction. Specifically, to adjust instruction, teachers should be monitoring specific skills, particularly for students below benchmark; identifying skill deficits to target with instruction; and using data to inform decisions on when to adjust intervention intensity. There are several potential reasons that could explain this finding. First, the use of data for instructional decision-making requires a more nuanced skill-set than using data to identify struggling learners, which may require even more intensive training than that provided (e.g., Mandinach & Gummer, 2016). In addition to more intensive training, it could be that the format of training did not lend itself to the use of data to guide instructional decisions. Although the format of training was not provided as a survey item, it has been noted that collaborative trainings are particularly important for data-focused trainings (e.g., Filderman et al., 2019; Datnow & Hubbard, 2016; Wayman & Jimerson, 2014). It is possible that the training provided was not collaborative or intensive enough; however, further research that explores training with a focus on using data to guide instruction is needed to determine how to promote the efficacy of this important training topic.

Finally, training provided in teacher preparation programs also comes into light as an important consideration in

Table 4. Odds Ratios for Benchmark Outcome.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Reading	*n* = 3,660	*n* = 3,520	*n* = 3,370	*n* = 3,160	*n* = 2,830
DI: One	1.63 (.30)*	1.62 (.31)*	1.67 (.31)**	1.69 (.38)*	1.68 (.36)*
DI: Two	1.88 (.40)**	1.94 (.42)**	2.08 (.46)**	1.98 (.44)**	2.13 (.51)**
DI: Three to four	2.29 (.52)***	2.28 (.52)***	2.31 (.54)***	2.25 (.56)**	2.23 (.56)**
DI: More than four	2.28 (.66)**	2.39 (.69)**	2.22 (.65)**	2.18 (.69)**	2.19 (.70)*
DG: One	1.15 (.17)	1.18 (.17)	1.06 (.16)	1.09 (.17)	1.03 (.18)
DG: Two	0.98 (.20)	0.99 (.20)	0.90 (.18)	0.83 (.18)	0.80 (.18)
DG: Three to four	0.95 (.20)	0.96 (.20)	0.92 (.19)	0.95 (.23)	0.90 (.21)
DG: More than four	1.07 (.26)	1.02 (.24)	1.03 (.26)	0.88 (.23)	0.80 (.22)
Assessment course	1.27 (.12)**	1.28 (.12)**	1.33 (.13)**	1.37 (.13)**	1.46 (.16)**
Math	*n* = 3,620	*n* = 3,480	*n* = 3,290	*n* = 3,130	*n* = 2,770
DI: One	1.13 (.15)	1.19 (.16)	1.15 (.16)	1.07 (.16)	1.11 (.17)
DI: Two	1.14 (.18)	1.17 (.19)	1.17 (.20)	1.07 (.19)	1.14 (.22)
DI: Three to four	1.33 (.28)	1.41 (.31)	1.39 (.33)	1.23 (.25)	1.35 (.32)
DI: More than four	1.77 (.51)*	1.94 (.60)*	1.72 (.51)	1.54 (.49)	1.51 (.51)
DG: One	1.24 (.21)	1.25 (.21)	1.21 (.20)	1.32 (.25)	1.30 (.23)
DG: Two	1.30 (.24)	1.27 (.24)	1.25 (.25)	1.33 (.26)	1.25 (.27)
DG: Three to four	1.29 (.26)	1.29 (.27)	1.26 (.30)	1.58 (.30)*	1.51 (.31)*
DG: More than four	1.81 (.40)**	1.64 (.38)*	1.80 (.40)**	1.84 (.43)**	1.73 (.41)*
Assessment course	1.42 (.12)***	1.43 (.13)***	1.43 (.13)***	1.37 (.12)***	1.36 (.12)**

Source. U.S. Department of Education, *Early Childhood Longitudinal Study, Kindergarten Class of 2010-11* (*ECLS-K:2011*), *Restricted Dataset.*
Note. Scale 0 = *Never*, 1 = *Once*, 2 = *two times*, 3 = *three to four times*, 4 = *more than four times; reference group* = 0. Model 2: teacher covariates include self-efficacy, years of experience, certification type, and highest education level obtained; Model 3: student covariates include race, disability status, English Learner status, gender, and risk status for reading or math; Model 4: school covariates include availability of support staff and Title 1 status; Model 5 is a fully conditional model that controls for all student, teacher, and school covariates. Not all teachers responded to each item, leading to different numbers of respondents for each model. DI = PD to use data to identify skill deficits; DG = PD to use data to guide instruction; PD = professional development.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

teacher use of data. Across all of the outcomes for both content areas, having taken a course geared toward the use of assessment data proved to be associated with increased reports of frequent use of data. Again, there are several reasons why taking a course may be increasingly important. First, it is possible that the higher intensity of a course (i.e., more than 20 hr of training on a specific topic; Darling-Hammond et al., 2009; Desimone, 2009; Guskey & Yoon, 2009) lead to more teacher learning and, correspondingly, use of skills learned in practice. Although it is possible that for some training topics, such as identifying struggling learners, fewer sessions are needed, for more intensive topics, such as data use to guide instruction and to make systematic decisions for intervention intensification, more intensive trainings may be necessary. Second, it is possible that teachers receiving coursework during preservice preparation programs more readily adopt practices, as it has been demonstrated that new teachers are more likely to adopt new practices (Boardman et al., 2005). Finally, it is possible that teachers who took courses on this topic attended institutions that emphasized the use of data. This could have two potential impacts on teacher data use: teachers may already have been using data as a part of their practice, and it could have impacted their beliefs surrounding data use. As beliefs have been found to be particularly important for teacher use of newly learned practices (Boardman et al., 2005), as well as for data-specific practices (Datnow & Hubbard, 2016; Wayman & Jimerson, 2014), it is possible that beliefs are partially responsible for increased reports of data use. The finding that coursework was associated with more frequent data use across outcomes may promote data-focused coursework as a way to improve teacher data use.

Mathematics and reading instruction. Results also differed based on academic content area. Namely, for math instruction, increases in data use were not consistent across outcomes, more training sessions were needed to observe these effects, and PD to use data to guide instruction significantly predicted use of data to monitor students who performed below benchmark. Each of these findings could be due to fewer studies being available on the use of data to intensify math instruction (Jung et al., 2018; Shapiro et al., 2005). As less is known about appropriate measurement and goals for monitoring progress in this content area (Shapiro et al., 2005), teachers may have required more training due to a lack of previous exposure and

Table 5. Odds Ratios for Placement Outcome.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Reading	n = 3,660	n = 3,520	n = 3,370	n = 3,160	n = 2,830
DI: One	1.90 (.38)*	1.86 (.40)**	1.93 (.40)*	1.84 (.40)**	1.89 (.45)**
DI: Two	2.09 (.40)***	2.05 (.41)***	2.16 (.44)***	1.95 (.40)**	2.05 (.47)**
DI: Three to four	2.18 (.48)**	2.13 (.48)**	2.06 (.48)**	2.06 (.49)**	2.02 (.51)**
DI: More than four	3.01 (.81)***	2.78 (.77)***	2.83 (.80)***	2.71 (.74)***	2.55 (.77)**
DG: One	1.02 (.16)	1.03 (.16)	0.97 (.16)	1.01 (.16)	0.94 (.16)
DG: Two	0.86 (.16)	0.87 (.17)	0.84 (.17)	0.87 (.19)	0.84 (.19)
DG: Three to four	0.97 (.21)	0.96 (.21)	0.94 (.22)	1.04 (.26)	0.95 (.25)
DG: More than four	1.02 (.24)	1.07 (.25)	1.03 (.26)	0.99 (.25)	0.99 (.27)
Assessment course	1.22 (.10)*	1.17 (.10)	1.21 (.10)*	1.28 (.25)**	1.25 (.12)*
Math	n = 3,610	n = 3,470	n = 3,280	n = 3,120	n = 2,760
DI: One	1.22 (.16)	1.28 (.17)	1.25 (.17)	1.24 (.17)	1.28 (.19)
DI: Two	1.25 (.19)	1.29 (.20)	1.28 (.19)	1.18 (.21)	1.27 (.24)
DI: Three to four	1.37 (.25)	1.41 (.27)	1.42 (.27)	1.22 (.23)	1.38 (.28)
DI: More than four	2.04 (.48)**	2.23 (.55)**	2.09 (.50)**	1.82 (.45)*	2.05 (.53)**
DG: One	1.19 (.19)	1.20 (.20)	1.15 (.18)	1.21 (.21)	1.19 (.20)
DG: Two	1.16 (.19)	1.13 (.20)	1.08 (.18)	1.21 (.22)	1.09 (.22)
DG: Three to four	1.25 (.24)	1.23 (.23)	1.20 (.24)	1.53 (.30)*	1.36 (.29)
DG: More than four	1.56 (.39)	1.44 (.37)	1.47 (.39)	1.65 (.45)	1.43 (.41)
Assessment course	1.49 (.13)***	1.46 (.13)***	1.47 (.14)***	1.48 (.13)***	1.41 (.13)***

Source. U.S. Department of Education, *Early Childhood Longitudinal Study, Kindergarten Class of 2010-11* (*ECLS-K:2011*), *Restricted Dataset.*
Note. Scale 0 = *Never*, 1 = *Once*, 2 = *two times*, 3 = *three to four times*, 4 = *more than four times; reference group* = 0. Model 2: teacher covariates include self-efficacy, years of experience, certification type, and highest education level obtained; Model 3: student covariates include race, disability status, English Learner status, gender, and risk status for reading or math; Model 4: school covariates include availability of support staff and Title 1 status; Model 5 is a fully conditional model that controls for all student, teacher, and school covariates. Not all teachers responded to each item, leading to different numbers of respondents for each model. DI = PD to use data to identify skill deficits; DG = PD to use data to guide instruction; PD = professional development.
*$p < .05$. **$p < .01$. ***$p < .001$.

learning entirely new content. This also would support the finding that training to guide instruction was associated with increased data use frequency for only the benchmark outcome, that is, it is possible that teachers were not previously aware of the specific math measurements that could be used to track progress, and therefore exposure to brief standardized measurements through this more specialized training increased teacher use of these measurements for tracking students below benchmark. This is particularly possible when considering the outcome of monitoring students below benchmark, as this outcome is uniquely primarily related to Tier 2 intervention as opposed to Tier 3 intensive intervention, on which less research has been conducted (Shapiro et al., 2005). As legislation and research emphasize the need for data use for both reading and math, it is essential to determine how to improve data training effects for math instruction.

Limitations

As with much research that conducts secondary analyses, this study is limited by the survey items. One limitation of the survey items is that they rely on teacher self-report of their use of data. Although there are potential limitations associated with self-report, the most important of which is that actual use of data is not measured, self-report data has been found to be indicative of reported behaviors and has construct validity that matches if not exceeds those used in observational measurements (Chan, 2009). Moreover, observational data in itself has been found to have similar weaknesses, including struggles to meet inter-rater reliability and disagreements on the frequency and duration of observations needed to capture behaviors (Hill et al., 2012). For these reasons, discrepancies between reported data use and actual data use are minimal when considering the other methods for capturing this construct. Another limitation of many secondary data analyses that does not escape the present study is related to survey questions. Although the questions provided an important lens into how often teachers are using data for various purposes, the questions did not directly ask whether data were being used to adjust instruction for struggling students, or how data were being used to guide these decisions. The lack of specificity on the specific content or format of the training also limits conclusions that can be drawn.

Future Directions

Although these findings provide insight into the role of training on teachers' use of data, future research is needed to address each of the noted limitations of the present study. First, research is needed that causally explores the relationship between training and data use, as well as the content and format of training sessions that further improve data use outcomes. To pursue this line of research, the development of more precise and replicable survey or observational measures of teacher use of data to guide instructional decisions in practice would provide additional insight into the more intensive uses of data in the classroom. By exploring the practical implications of data literacy training further, we can better understand what supports teachers need to use data effectively which will lead to improved student outcomes.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported in part by grant H325D150056 from the Office of Special Education Programs, U.S. Department of Education. These contents do not necessarily represent the policy of this agency, and one should not assume endorsement by the federal government.

Supplemental Material

Supplemental material for this article is available online at https://journals.sagepub.com/doi/suppl/10.1177/1534508420902523.

References

Abedi, J., & Gándara, P. (2006). Performance of English language learners as a subgroup in large-scale assessment: Interaction of research and policy. *Educational Measurement: Issues and Practice*, *25*(4), 36–46.

Ardoin, S. P., Christ, T. J., Morena, L. S., Cormier, D. C., & Klingbeil, D. A. (2013). A systematic review and summarization of the recommendations and research surrounding curriculum-based measurement of oral reading fluency (CBM-R) decision rules. *Journal of School Psychology*, *51*(1), 1–18.

Balu, R., Zhu, P., Doolittle, F., Schiller, E., Jenkins, J., & Gersten, R. (2015). *Evaluation of response to intervention practices for elementary school reading* (NCEE 2016-4000). National Center for Education Evaluation and Regional Assistance.

Boardman, A. G., Argüelles, M. E., Vaughn, S., Hughes, M. T., & Klingner, J. (2005). Special education teachers' views of research-based practices. *The Journal of Special Education*, *39*, 168–180.

Chan, D. (2009). So why ask me? Are self-report data really that bad. In C. Lance & R. Vandenberg (Eds.), *Statistical and methodological myths and urban legends: Doctrine, verity and fable in the organizational and social sciences* (pp. 309–336). Routledge.

Civic Impulse. (2017). H.R. 1532 (112th) congress: Race to the Top Act of 2011. https://www.govtrack.us/congress/bills/112/hr1532

Council of Chief State School Officers. (2013). *Interstate Teacher Assessment and Support Consortium (InTASC) model core teaching standards and learning progressions for teachers 1.0*. Washington, D.C.

Darling-Hammond, L., Wei, R. C., Andree, A., Richardson, N., & Orphanos, S. (2009). *Professional learning in the learning profession*. National Staff Development Council.

Datnow, A., & Hubbard, L. (2016). Teacher capacity for and beliefs about data-driven decision making: A literature review of international research. *Journal of Educational Change*, *17*, 7–28.

Desimone, L. M. (2009). Improving impact studies of teachers' professional development: Toward better conceptualizations and measures. *Educational Researcher*, *38*(3), 181–199.

Espin, C. A., Wayman, M. M., Deno, S. L., McMaster, K. L., & de Rooij, M. (2017). Data-based decision-making: Developing a method for capturing teachers' understanding of CBM graphs. *Learning Disabilities Research & Practice*, *32*(1), 8-21.

Every Student Succeeds Act. (2015). Pub. L. No. 114-95. In *114th Congress*.

Filderman, M. J., Toste, J. R., Didion, L. A., & Peng, P. (2019). Data Literacy Training for K-12 Teachers: A Meta-Analysis of the Effects on Teacher Outcomes. Manuscript submitted for publication.

Fuchs, L. S., Fuchs, D., Hamlett, C. L., Phillips, N. B., & Bentz, J. (1994). Classwide curriculum-based measurement: Helping general educators meet the challenge of student diversity. *Exceptional Children*, *60*(6), 518–537.

Fuchs, L. S., Fuchs, D., & Stecker, P. M. (1989). Effects of curriculum-based measurement on teachers' instructional planning. *Journal of Learning Disabilities*, *22*(1), 51–59.

Fuchs, D., Fuchs, L. S., & Compton, D. L. (2012). Smart RTI: A next-generation approach to multilevel prevention. *Exceptional Children*, *78*, 263–279.

Gallagher, L., Means, B., & Padilla, C. (2008). *Teachers' use of student data systems to improve instruction: 2005 to 2007*. https://www2.ed.gov/rschstat/eval/tech/teachers-data-use-2005-2007/teachers-data-use-2005-2007.pdf

Guskey, T. R. (2002). Professional development and teacher change. *Teachers and Teaching: Theory and Practice*, *8*, 381–391.

Guskey, T. R., & Yoon, K. S. (2009). What works in professional development? *Phi Delta Kappan*, *90*, 495–500.

Hill, H. C., Charalambous, C. Y., & Kraft, M. A. (2012). When rater reliability is not enough: Teacher observation systems and a case for the generalizability study. *Educational Researcher*, *41*(2), 56–64.

Hoogland, I., Schildkamp, K., van der Kleij, F., Heitink, M., Kippers, W., Veldkamp, B., & Dijkstra, A. M. (2016). Prerequisites for data-based decision making in the classroom: Research evidence and practical illustrations. *Teaching and Teacher Education*, *60*, 377–386.

Hoover, N. R., & Abrams, L. M. (2013). Teachers' instructional use of summative student assessment data. *Applied Measurement in Education*, *26*, 219–231.

Individuals with Disabilities Education Improvement Act of 2004, P.L. 108–446.

Ingram, D., Seashore, K., & Schroeder, R. (2004). Accountability policies and teacher decision making: Barriers to the use of data to improve practice. *Teachers College Record*, *106*, 1258–1287.

Jung, P. G., McMaster, K. L., Kunkel, A. K., Shin, J., & Stecker, P. M. (2018). Effects of data-based individualization for students with intensive learning needs: A meta-analysis. *Learning Disabilities Research & Practice*, *33*, 144–155.

Lai, M. K., & McNaughton, S. (2016). The impact of data use professional development on student achievement. *Teaching and Teacher Education*, *60*, 434–443.

Mandinach, E. B., & Gummer, E. S. (2016). What does it mean for teachers to be data literate: Laying out the skills, knowledge, and dispositions. *Teaching and Teacher Education*, *60*, 366–376.

Means, B., Chen, E., DeBarger, A., & Padilla, C. (2011). *Teachers' ability to use data to inform instruction: Challenges and supports*. https://www2.ed.gov/rschstat/eval/data-to-inform-instruction/report.doc

Schildkamp, K., & Kuiper, W. (2010). Data-informed curriculum reform: Which data, what purposes, and promoting and hindering factors. *Teaching and Teacher Education*, *26*, 482–496.

Shapiro, E. S., Edwards, L., & Zigmond, N. (2005). Progress monitoring of mathematics among students with learning disabilities. *Assessment for Effective Intervention*, 30(2), 15–32.

Share, D. L., & Silva, P. A. (2003). Gender bias in IQ-discrepancy and post-discrepancy definitions of reading disability. *Journal of Learning Disabilities*, *36*(1), 4–14.

Spear-Swerling, L., & Cheesman, E. (2012). Teachers' knowledge base for implementing response-to-intervention models in reading. *Reading and Writing*, *25*, 1691–1723.

Supovitz, J. A., & Klein, V. (2003). *Mapping a course for improved student learning: How innovative schools systematically use student performance data to guide improvement* [CPRE research reports]. https://repository.upenn.edu/cpre_researchreports/39/

Tourangeau, K., Nord, C., Lê, T., Sorongon, A. G., Hagedorn, M. C., Daly, P., & Najarian, M. (2015). *Early Childhood Longitudinal Study, Kindergarten Class of 2010-11 (ECLS-K:2011). User's manual for the ECLS-K:2011 kindergarten data file and electronic codebook, public version* (NCES 2015-074). National Center for Education Statistics, U.S. Department of Education.

Van den Bosch, R. M., Espin, C. A., Chung, S., & Saab, N. (2017). Data-Based Decision-Making: Teachers' Comprehension of Curriculum-Based Measurement Progress-Monitoring Graphs. *Learning Disabilities Research & Practice*, *32*(1), 46–60.

Wagner, D. L., Hammerschmidt-Snidarich, S. M., Espin, C. A., Seifert, K., & McMaster, K. L. (2017). Pre-service teachers' interpretation of CBM progress monitoring data. *Learning Disabilities Research & Practice*, *32*(1), 22-31.

Wayman, J. C., & Jimerson, J. B. (2014). Teacher needs for data-related professional learning. *Studies in Educational Evaluation*, *42*, 25–34.

Zhang, D., Katsiyannis, A., Ju, S., & Roberts, E. (2014). Minority representation in special education: 5-year trends. *Journal of Child and Family Studies*, *23*(1), 118–127.