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Teacher Predictors of Student Progress in Data-Based Writing Instruction: Knowledge, Skills, Beliefs, and Instructional Fidelity

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Abstract

Teacher-level factors are theoretically linked to student outcomes in data-based instruction (DBI; Lembke et al., 2018). Professional development and ongoing support can increase teachers' knowledge, skills, and beliefs related to DBI, as well as their instructional fidelity (McMaster et al., 2020). However, less is known about how each of these teacher-level factors influences student progress during an intervention. The purpose of this study was to examine the association between several important teacher-level factors—teachers' writing instruction fidelity, knowledge and skills related to DBI, explicit writing orientation, and writing instruction self-efficacy—and students' writing growth. Participants were 49 U.S. elementary teachers and their 118 students struggling with early writing skills. Using hierarchical linear modeling, we found a significant positive relation between DBI knowledge and skills and student writing growth, but no relation was found between writing instruction fidelity, writing orientation, or self-efficacy and student writing growth. Implications for writing instruction fidelity measurement in DBI and professional development related to teachers' DBI knowledge and skills are discussed.

Keywords

CBM, written language, teacher education/preparation

Teachers' use of data-based instruction (DBI; Deno & Mirkin, 1977), a framework for analyzing student data and making instructional decisions, can increase writing outcomes for elementary writers with significant learning difficulties (Jung et al., 2017; McMaster et al., 2020). Despite its efficacy, the extent to which teachers implement DBI to meet their struggling learners' needs varies considerably (Lemons et al., 2016). Teacher-level factors, including knowledge and skills related to DBI and instructional fidelity, are theoretically linked to student outcomes (Lembke et al., 2018). However, empirical evidence for the impact of teacher factors on student DBI outcomes is mixed (Bresina & McMaster, 2020). Without a clear understanding of which teacher factors influence students' progress through DBI, writing success for high-need elementary students may remain elusive.

The purpose of this study was to identify teacher-level factors related to student growth in DBI for writing. Our hypothesis was that:

> **Hypothesis 1 (H1):** Teachers' writing instruction fidelity, knowledge and skills related to DBI, and instructional beliefs (personal self-efficacy and explicit writing orientation) would be associated with students' writing growth.

This hypothesis was primarily informed by research demonstrating that these factors influence student intervention outcomes (e.g., Bresina & McMaster, 2020; Durlak & DuPre, 2008). We expect that identifying relations between teacher predictors and student intervention progress will positively affect the design and refinement of DBI professional development (PD).

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Data-Based Instruction

Developed initially by Stanley Deno and colleagues (e.g., Deno & Mirkin, 1977; Fuchs et al., 2014), DBI is a framework that teachers apply to evaluate and modify interventions for students who require the most individualized instruction. Research indicates that DBI is an effective means of improving targeted academic outcomes (Filderman et al., 2018; Jung et al., 2018), including writing (Jung et al., 2017). To implement DBI, a teacher will typically: (a) establish a student's present level of performance on a target skill; (b) set a long-term goal; (c) implement instruction; (d) monitor progress toward the goal; (e) determine if an instructional change is needed; (f) hypothesize about students' needs and changing instruction accordingly; (g) monitor progress to evaluate the effectiveness of changes; and (h) continue this process until the student meets their goal (Jung et al., 2018). Teachers use three components in DBI: intensive instruction, curriculum-based measurement (CBM; Fuchs et al., 1984), and data-based decision-making (DBDM).

Although many standard instructional interventions are broadly effective, they may not always be effective for the smaller subset of students with significant learning difficulties, including students with learning disabilities. These students often require intensive intervention, meaning academic programing that is explicit, delivered at a high dosage in a small group (Wanzek et al., 2018; Wanzek & Vaughn, 2008), and individualized (Fuchs et al., 2014). Individualization includes shifting the focus or methods of instruction to better meet a student's needs (e.g., Fuchs et al., 2018).

During intensive intervention, special educators conduct ongoing assessment to monitor students' progress, often using CBM. Curriculum-based measurement is an approach developed by Deno and colleagues (Deno, 1985) with the purpose of providing general indicators of academic performance and growth. With CBM, teachers can administer brief, equivalent measures frequently (e.g., weekly) to monitor student progress toward a goal and to inform instruction. Researchers have demonstrated that CBM Writing (CBM-W) can provide reliable and valid data of overall early writing performance (e.g., Allen et al., 2020).

DBDM is the elemental component of DBI. To determine whether interventions are effective, teachers analyze students' graphed CBM data. Scores from CBM tasks are entered on a graph that includes the students' baseline data, their goal for ending level of performance, and the expected rate of growth to meet that goal. Teachers examine students' actual rate of improvement, or slope, in comparison with their goal line (e.g., Jenkins & Terjeson, 2011). Based on the findings of this comparison, teachers may continue the intervention (if the student slope is in line with the goal line), raise the goal (if the student slope is above the goal line), or change the intervention (if the student slope is below the goal line; Stecker et al., 2005). Thus, DBDM allows teachers to create individualized interventions that lead to improved outcomes for students (Stecker et al., 2005).

Implementing DBI

As the previous description of DBI illustrates, the process is complex and iterative. As a result, many teachers struggle with implementation. Teachers often perform poorly on CBM interpretation tasks, incorrectly apply DBDM rules, and make inaccurate hypotheses for students' lack of progress (van den Bosch et al., 2017; Wagner et al., 2017). As a result, many teachers have difficulty planning and enacting effective instructional decisions using CBM data (Stecker et al., 2005).

These difficulties may be a result of insufficient DBI training. Teacher preparation programs often provide minimal training related to intensive intervention (Fuchs et al., 2012; Wagner et al., 2017). For example, while CBM implementation has increased in the past 20 years, special education teachers continue to report a need for PD on using CBM data (Swain & Hagaman, 2020). Findings from a recent national survey also indicate that, on average, teachers receive only 2.5 hr of PD related to making intensification decisions (Oslund et al., 2021). Teachers, therefore, require more training and PD support to implement DBI.

Teachers benefit from PD as they engage in the DBI process, but improvements in PD quality are needed. Educator support has a positive effect on both educator- and student-level academic intervention outcomes in general (e.g., Brock et al., 2017). Students of teachers who receive DBI PD and coaching during the DBI implementation process also can experience increased academic outcomes compared with students whose teachers did not (e.g., Allinder et al., 2000). This effect is likely because PD can positively affect teachers' knowledge, skills, and beliefs related to DBI (Gesel et al., 2021). However, recent evidence also suggests that teachers' PD experience related to DBDM does not always predict their ability to make data-based decisions (Oslund et al., 2021). This finding implies that consistent, effective approaches to supporting teachers' use of DBI are needed.

Teacher-Level Factors and Student Outcomes in DBI

To develop an effective PD system for teachers implementing DBI in early writing, it is critical to consider potential links between several teacher-level factors and student outcomes (Lembke et al., 2018). First, *teachers' knowledge and skills related to DBI* may be associated with students' progress during intervention. Teachers' content knowledge has been consistently linked to students' academic outcomes (e.g., Cunningham et al., 2004). However, DBI implementation requires teachers to be knowledgeable not only about instructional content but also the instructional decision-making process (e.g., Stecker et al., 2005). Teachers' ability to interpret CBM graphs and their knowledge of how to make instructional changes are related to accurate DBDM (Fuchs et al., 1984; Stecker et al., 2005), which may increase the likelihood of students' response to intervention. However, more research is needed to examine whether this theoretical association between teachers' knowledge, and skills related to DBI and their students' responsiveness to intervention exists.

Second, *teachers' writing orientation*, or their theoretical perspective on how to best develop students' writing skills, likely influences how and what teachers choose to teach (Graham et al., 2002; Troia et al., 2011). Elementary teachers' explicit writing orientation is associated with their use of explicit instruction but may not predict the writing growth of elementary students in general (Rietdijk et al., 2018; Ritchey et al., 2015). Explicit instruction is particularly effective for students with academic difficulties, including writing difficulties (e.g., McMaster et al., 2018). Thus, research on the effects of teachers' explicit instruction orientation on the progress of students with writing difficulties is needed.

Third, *teacher instructional self-efficacy*, or "confidence that they can perform the actions that lead to student learning" (Graham et al., 2001, p. 178), affects the extent to which teachers persist and succeed in helping students with learning difficulties, and predicts student CBM slope in math intervention (Allinder, 1994, 1995). Examining whether these effects hold in other intervention contexts, such as DBI in writing, is a necessary step to determine whether teachers' self-efficacy should be targeted in PD.

Fourth, *instructional fidelity*, or the degree to which an intervention is implemented as intended (Yeaton & Sechrest, 1981), has been found to positively predict student intervention outcomes (Durlak & DuPre, 2008). In the context of DBI, instructional fidelity is the extent to which teachers adhere to instructional steps, as well as implement individualized elements of interventions, as intended (e.g., Harn et al., 2013; Johnson & McMaster, 2013). When teachers receive support to improve their implementation of individualized reading interventions, this support is associated not only with increased instructional fidelity, but also increased student reading outcomes (Brownell et al., 2017). Thus, it is possible that instructional fidelity in DBI is associated with improved student writing outcomes.

Bresina and McMaster (2020) explored the relation between teacher-level factors and elementary student writing progress in the context of a DBI PD program (McMaster et al., 2020). Data-based instruction knowledge and skills were strongly related to student CBM slope, and there was a negative relation between writing instruction fidelity and CBM slope. This second finding may indicate that fidelity was not measured in a sensitive enough manner to capture intensive intervention fidelity. Additionally, due to small sample size, the authors were not able to account for the nested nature of the CBM data in their analysis. Although these findings provide preliminary evidence for the effect of knowledge and skills on the growth of students in DBI, more research is needed to determine whether additional teacher-level factors contribute to students' progress.

Present Study

The aim of this study was to identify teacher characteristics associated with student growth (CBM-W slope) in early writing DBI. Using data from a multi-year DBI PD efficacy trial, we aimed to replicate and extend the findings of Bresina and McMaster (2020). First, we intended to test the tenability of the relation between teachers' DBI knowledge and skills and student growth by accounting for the non-independence of student data (nested within teachers) and including a larger sample size. Second, we used a writing instruction fidelity tool that was revised to account for multiple dimensions of fidelity, which may have increased the likelihood of identifying a relation with student growth. Third, we included additional teacher-level variables related to teachers' instructional beliefs as predictors. Thus, this study was guided by the following research question:

> **Research Question 1 (RQ1):** To what extent do teachers' writing instruction fidelity, knowledge and skills related to DBI, and beliefs predict student CBM-W slope?

Method

Data used in this study were drawn from an ongoing randomized control trial evaluating the effects of PD on teachers' use of DBI for early writing, the Early Writing Project (EWP). In the EWP, three cohorts of teachers across 3 years were randomly assigned to a treatment or control group. Given that only treatment teachers monitored student progress, only these participants were included in this study. Furthermore, because the third year of the EWP was affected by the COVID-19 pandemic, some students in Cohort 3 had substantially different CBM progress monitoring data from Cohorts 1 and 2 (i.e., extended periods of absences); thus, Cohort 3 was not included.

Setting and Participants

The larger study was conducted in 14 urban, suburban, and rural school districts in two U.S. Midwestern states during the 2018-19 and 2019-20 school years. To participate in the

Table 1. Demographics for Teacher Participants in the Predictors of Student Progress Study.

Demographic	*n*	%
Gender		
Female	47	95.9
Male	2	4.1
Ethnicity		
Black/African American	2	4.1
Multi-Racial	4	8.2
White	44	89.8
Prefer not to respond	1	2.0
Highest degree		
Bachelor's	11	22.4
Master's	20	40.8
Master's + coursework	17	34.7
Ed.S.	1	2.0
Current job title		
Intervention teacher	1	2.0
Special education teacher	47	95.9
Other	1	2.0
	M (range)	
Years teaching	10.4 (1.0, 32.0)	

Table 2. Demographics for Student Participants in the Predictors of Student Progress Study.

Demographic	*n*	%
Ethnicity		
Asian	2	1.7
Black/African American	22	18.6
Hispanic/Latinx	16	13.6
Multi-Racial	2	1.7
Native American/Alaskan Native	4	3.4
White	68	57.6
Other	1	0.8
Not reported	3	2.5
Special education primary category		
Autism	15	12.7
Deaf-blind	1	0.9
Deaf/hard of hearing	3	2.5
Emotional/behavioral disorder	9	7.6
Intellectual disability	10	8.5
Specific learning disability	29	24.6
Speech/language impairment	7	5.9
Needing alternative programing	11	9.3
Other health impairment	27	22.9
None	4	3.4

EWP, teachers needed to (a) directly support elementary students at risk for or with disabilities who experienced difficulty in writing and (b) have at least 2 years of teaching experience. Forty-nine teachers were assigned randomly to the treatment condition and were the teacher participants of this study. For teacher demographics, see Table 1.

Teachers, who included special educators and interventionists, nominated their elementary students in need of intensive writing intervention. Although we aimed to include students in early elementary grades (Grades K–3), we also allowed teachers, to a limited degree, to nominate their students in Grades 4 and 5 in need of intensive writing support. Nominated students were screened using two forms each of two CBM-W tasks: word dictation (WD) and picture word (PW). Researchers then selected the two to three students who scored lowest on both measures for study participation. After screening, 136 treatment students were eligible; complete data were available for 118 students (13.2% attrition). Missingness was due to withdrawal (n = 8) or not having CBM graphs available (n = 5). Failure to collect CBM graphs was related to challenges associated with the start of the COVID-19 pandemic (Cohort 2). Independent t tests for CBM pretest scores confirmed that writing skills of students with complete and incomplete data were similar (all p values above .57). Students with missing data were dropped from analyses using listwise deletion. Of the student participants, 65.3% (n = 77) were male, 65.1% (n = 58) received free/reduced-price lunch services, and 13.6% (n = 16) received English language services. Students were in kindergarten (n = 2, 1.7%) and Grades 1 (n = 24, 20.3%), 2 (n = 25, 21.2%), 3 (n = 40, 33.9%), 4 (n = 19, 16.1%), and 5 (n = 8, 6.8%). For additional student demographics, see Table 2.

Measures

Curriculum-based measures in writing

Measures and scoring protocols. To measure student progress during a writing intervention, teachers selected one of three CBM-W tasks: WD, PW, or story prompt (SP). Each CBM task includes multiple scoring procedures to capture varying levels of complexity of students' writing (including correct letter sequences [CLS] and correct word sequences [CWS]). Word dictation CLS are two adjacent letters the student correctly places according to the correct spelling of a dictated word (Deno et al., 1980). Picture word CWS are any two adjacent words spelled and used correctly in sentences that students write based on a series of pictures (Videen et al., 1982). CWS was also the SP score used in this study. Word dictation, PW, and SP alternate-form reliability has ranged from r = .60 to .94 in Grades 1–3 (Allen et al., 2020; Hampton & Lembke, 2016; McMaster et al., 2011). SP CWS alternate-form reliability for students Grades 2 to 5 has ranged from r = .70 to .80 (McMaster et al., 2017). In this sample, alternate-form reliability (based on CBM scores collected in Weeks 1 and 2) ranged from r = .60 to .94.

Slope. Curriculum-based writing measures have produced slopes sensitive to student growth within 8 weeks (Hampton

& Lembke, 2016; McMaster et al., 2011, 2017). In this study, CBM slope was students' CBM-W rate of improvement over 20 weeks of intervention (calculated using lm package in R). Teachers selected WD CLS (n = 79, 66.9%), PW CWS (n = 30, 25.4%), or SP CWS (n = 9, 7.6%). We transformed slopes into one outcome variable by converting them to z-scores within groups of students monitored with the same CBM task. The CBM tasks may appear to represent distinct skills, but scores were moderately to strongly correlated at pre- (r = .73 to .77) and post-test (r = .65 to .76) in the larger EWP study. The scores may, therefore, represent one construct of early writing ability and were thus combined for this study. Curriculum-based measurement slope z-scores ranged from −3.30 to 3.33 for WD CLS, −2.10 to 1.52 for PW CWS, and −1.70 to 1.50 for SP CWS.

Predictors

CBM baseline. In prior studies, students with lower pretreatment, or baseline, scores have been found to display more growth during intensive intervention (e.g., Hendricks & Fuchs, 2020). We controlled for the potential influence of baseline scores on slope by including CBM baseline z-scores as a predictor in our models. Curriculum-based measurement baseline was the median score of three initial, consecutive administrations. Curriculum-based measurement baseline z-scores ranged from −1.35 to 2.50 for WD CLS, −1.55 to 2.87 for PW CWS, and −0.91 to 1.75 for SP CWS.

Writing instruction fidelity. We measured teachers' fidelity of writing instruction via direct observation. The writing instruction fidelity form (see online supplemental material S1) is a checklist of steps for implementation of components of explicit and intensive writing instruction (e.g., modeling, guided practice with feedback, independent practice). The measure also captures student participation in instruction (e.g., on-task behavior). Teachers' instruction was observed in-person, and they were aware of their observations beforehand. Teachers received points for each step on a scale of 0 (not observed) to 2 (fully observed). We evaluated fidelity in this manner to capture the flexibility of implementation that can lead to intended student outcomes in individualized instruction (e.g., Johnson & McMaster, 2013). In the larger EWP study, teachers created individualized lesson plans by selecting from researcher-created activities, or "mini-lessons." To capture individualized aspects of instruction, we included two to three fidelity items specific to each mini-lesson. For example, a sentence combining mini-lesson required teachers to "explain why the combined sentences sound better." The fidelity tool used in this study included a criterion of whether teachers completed all mini-lesson-specific fidelity items. Writing instruction fidelity was averaged to one final score across two time points (fall and spring). Average writing instruction fidelity ranged from 79% to 97% (M = 90.65%, SD = 3.83%).

Knowledge and skills. Teachers completed a measure of DBI knowledge and skills. The test includes multiple-choice questions related to domains of DBI in writing: the purpose of DBI, DBI steps, writing instruction, and using CBM data for DBDM. For example, teachers answered the multiple-choice question, "Who should receive DBI?" with one of the following choices: "all students," "students in need of Tier 3 intervention in a Response to Intervention (RTI) system," or "Choices 1 and 2." Cronbach's alpha coefficients were .56 and .62 at pretest for Cohorts 1 and 2, respectively. Only pretest scores were included in our analyses, as these scores reflect teachers' knowledge and skills at the beginning of students' intervention.

Self-efficacy. Teacher self-efficacy was assessed using Graham et al.'s (2001) Teacher Efficacy Scale. The personal efficacy scale measures teachers' confidence in their abilities to affect student writing. For example, teachers indicate the extent to which they agree with the statement, "When a student's writing performance improves, it is usually because I found more effective teaching approaches." Cronbach's alpha was .74 at pretest for Cohorts 1 and 2.

Writing orientation. Teachers' writing orientation was assessed with Graham et al.'s (2002) Writing Orientation Scale. The measure includes preference for explicit writing instruction as a subscale. This subscale includes statements such as, "It is important to teach students strategies for planning and revising." Cronbach's alpha was .60 at pretest for Cohorts 1 and 2. Only pre-test explicit writing orientation scores were included.

Procedures

Data collector training. Graduate research assistants (GRAs; all PhD students in school psychology or special education) monitored teachers' fidelity of CBM administration, CBM scoring reliability, and writing instruction fidelity. Graduate research assistants received 1 week of data collection training from primary investigators (PIs). They had to demonstrate 95% accuracy on a measure of CBM administration fidelity (Fuchs et al., 1984), and also needed to reach 85% CBM scoring reliability with project coordinators (PCs) on two samples of each task using point-by-point agreement. Project coordinators also checked 30% of scored samples to confirm ongoing reliability. Final agreement was above 90%. To monitor teacher writing instruction fidelity, GRAs needed to reach 80% interobserver agreement (IOA) with PIs on two sample videos. Interobserver agreement was also collected from 20% of each GRAs' teacher writing instruction fidelity observations, and final agreement was above 80%.

EWP implementation. Before receiving PD, teachers completed a pretest survey that included the teacher-level measures described in the Predictors section. Teachers then participated in two training modules (Modules 1 and 2) in August before school began. Then, teachers delivered instruction and collected student data across 20 weeks from September to April (not including breaks). During this time, they participated in two additional training modules (Module 3 in early fall, and Module 4 in winter). Modules 1 and 2 provided an overview of DBI, CBM-W, and writing intervention. During Module 3, teachers chose a CBM and scoring protocol for each student based on their writing performance. Teachers also selected from 12 EWP mini-lessons to create lesson plans individualized to their students' needs (see supplemental material S2 for description). These activities targeted transcription (e.g., spelling) or text generation (e.g., sentence construction) skills. Word dictation CLS students' instruction targeted text generation less frequently than PW or SP CWS students (12.8% versus 70.0%, respectively). After creating lesson plans, teachers began implementing writing instruction. Early Writing Project researchers recommended delivering instruction at least three times per week in 20-to-30-min sessions, but teachers ultimately decided intervention dosage. At this time, teachers also began collecting CBM data. In Module 4, teachers learned the process of DBDM using student CBM graphs. During the study, GRAs also provided biweekly coaching with problem-solving support, as well as CBM administration fidelity feedback twice, monthly CBM scoring reliability checks, and monthly writing instruction fidelity feedback.

Fidelity of teacher DBI implementation. Graduate research assistants monitored teachers' DBI fidelity (writing instruction, CBM, and DBDM). Teachers' fidelity of writing instruction averaged at 88.4% at Time 1 and 92.9% at Time 2. Teachers' CBM fidelity of administration, as measured by percentage of administration steps completed (Fuchs et al., 1984) was assessed in the fall (Time 1) and spring (Time 2). Curriculum-based measurement administration fidelity at Time 1 averaged at 90.6%, 92.4%, and 87.0% for WD, PW, and SP, respectively. At Time 2, fidelity averaged at 90.9%, 95.4%, and 88.5%. Teachers' monthly CBM scoring reliability, as measured by point-by-point agreement between teachers' CBM scoring and their coaches' scoring, ranged from 90.5% to 100%. Data-based decision-making fidelity, as measured by a percentage of two implementation dimensions (timeliness and appropriateness of the decision), averaged at 89.4% at Time 1 (early winter) and 86.1% at Time 2 (early spring; $n = 43$ teachers).

Analysis

We used hierarchical linear modeling (HLM; Raudenbush & Bryk, 2002) to estimate the effects of teacher-level predictors on CBM slope. Hierarchical linear modeling accounted for the clustering of students within teachers' caseloads/classrooms (Osborne, 2000). We created an initial that included a random effect of teachers and calculated the intraclass correlation (ICC) to determine the proportion of CBM slope variance attributable to teacher clusters. The ICC indicated that a substantial (Hox et al., 2010) amount of the variance in CBM slopes was between teachers (21.3%); therefore, use of HLM was tenable.

A model comparison approach was used to test the statistical significance of sequentially more complex models. Models were constructed using lme4 in R (Bates et al., 2015). Three model indices were used to determine improvement in fit from one model to the next: likelihood ratio (chi square), corrected Akaike information criterion (AICc), and Bayesian information criterion (BIC). If chi square was statistically significant and the AICc was reduced for a model, the model was considered significant. The BIC provided supplemental fit information, as the BIC includes a larger penalty term for the number of parameters included in the model than the AICc (Vrieze, 2012). Model comparisons served as omnibus tests for the parameters of each following model.

The base model (M1) was a random intercepts model that included a fixed effect of CBM baseline and a random effect of teacher. The subsequent models added teacher-level predictors with random intercepts. For predictors included in each model (M2 to 5), see Table 3. We examined the student and teacher-level residuals of models and found no model assumption violations.

Results

In this section, we present results from analyses of the effects of students' CBM baseline and teacher factors (writing instruction fidelity, knowledge and skills, personal self-efficacy, and explicit writing orientation) on student CBM slope. For correlations between predictors, see Table 4. Three correlations were significant ($p < .01$): CBM baseline and slope, teachers' self-efficacy and explicit writing orientation, and teachers' explicit writing orientation and writing instruction fidelity. However, no correlations were above the absolute value of 0.3.

Missing Teacher Data

Out of 49 teachers, three (6%) did not have Time 2 writing instruction fidelity scores. To calculate average writing instruction fidelity for these teachers, we inputted the sample average Time 2 fidelity score. We conducted a sensitivity analysis by comparing models fit to sample that provided the complete data (no missing Time 2 writing instruction fidelity data) with the full sample using imputed Time 2 writing instruction fidelity data. The results of these models did not differ significantly (i.e., the models of best fit and their significant effects were the same), suggesting that our models were insensitive to the presence of missing data. Thus, we used the imputed Time 2 writing instruction fidelity data in our final models.

Table 3. Taxonomy of Models Predicting CBM Slope Including Fixed Effects Coefficients (Standard Errors).

Coefficient	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	−.06 (0.10)	−1.63 (2.40)	−3.67 (2.50)	−4.56 (2.67)	−4.64 (2.61)
CBM baseline	−.24 (.10)*	−.24 (.10)*	−.27 (.10)*	−.27 (.10)*	−.28 (.10)*
Avg WI Fidelity		.02 (.03)	.03 (.03)	.03 (.03)	.04 (.03)
Pre KS DBI			.05 (.02)*	.05 (.02)	.05 (.02)*
Pre WO Explicit				.13 (.16)	.20 (.16)
Pre TES Personal					−.23 (.15)
ICC teacher	.760	.765	.755	.750	.744
AICc	323.211	325.072	323.208	324.867	325.000
Delta AICc	.003	1.864	.000	1.659	1.782
Log likelihood	−155.227	−155.028	−152.943	−152.600	−151.467
BIC	339.079	343.449	344.052	348.137	350.641

Note. Models fitted to predict CBM-W slope for 118 students in 49 teacher clusters. All models included random effects of teacher intercept and were fitted using maximum likelihood. Avg WI Fidelity = teachers' average writing instruction fidelity; CBM = curriculum-based measurement; ICC = intra-level correlation coefficient; AICc = corrected Akaike information criterion; BIC = Bayesian information criterion; Pre KS DBI = teachers' pretest DBI knowledge and skills; Pre TES Personal = teachers' pretest Teacher Efficacy Scales, personal efficacy; Pre WO Explicit = teachers' pretest explicit writing orientation. Delta AICc calculated based on model 3.
$^*p \le .05$.

Table 4. Correlations Between Predictors.

Variable	1	2	3	4	5	6
1. CBM Slope	1.000					
2. CBM Baseline	−.274**	1.000				
3. Avg WI Fidelity	.130	.047	1.000			
4. Pre KS DBI	.142	.063	−.195	1.000		
5. Pre WO Explicit	−.101	−.025	.124*	−.109	1.000	
6. Pre TES Personal	.134	−.042	−.080	.207	.220**	1.000

Note. Avg WI Fidelity = teachers' average writing instruction fidelity; CBM = curriculum-based measure; Pre KS DBI = teachers' pretest DBI knowledge and skills; Pre TES Personal = teachers' pretest Teacher Efficacy Scales, personal efficacy; Pre WO Explicit = teachers' pretest explicit writing orientation.
$^*p < .05$. $^{**}p < .01$.

Model Comparison

Table 3 shows the results and model comparison of the HLM models predicting CBM slope. In M1, the fixed effect of CBM baseline on CBM slope was significant (p = .02); for each one *SD* increase in CBM baseline, CBM slope decreased, on average, by 0.24 *SD*. M2 to M5 included the teacher-level variables as predictors. Among these models, M3 demonstrated the most evidence of model fit. M3 improved fit over M2 ($\chi^2_8 = 4.17$, p = .04), and the AICc was reduced. There was less evidence to support the relative improved fit of M3 over M1. The change in AICc was 0.003; this finding suggests that M1 is also plausible (Burnham et al., 2011). Additionally, the BIC was larger in M3 than M1, indicating that, when applying a more stringent penalty for model complexity, M1 was likely the model of best fit. However, given that there is some evidence that M3 was a candidate for best fit despite the inclusion of teacher-level variables, we considered the relations between these predictors and CBM slope worthy of examination.

Our research aim was to examine the extent to which student CBM-W slope varied as a function of teachers' writing instruction fidelity, knowledge and skills related to DBI, explicit writing orientation, and self-efficacy. M3 included only the teacher-level predictors of writing instruction fidelity and knowledge and skills related to DBI. The final model was as follows:

$$\begin{aligned} Y_{ij} = {} & \beta_{0j} + \beta_{1j}\text{CBM Baseline}_j + \\ & \beta_{2j}\text{Writing Instruction Fidelity}_j + \\ & \beta_{3j}\text{DBI Knowledge and Skills}_j + r_{ij} \end{aligned}$$

where Y_{ij} is the CBM slope of student i nested in teacher j, β_{0j} is the mean CBM slope plus the unique effect of teacher j, coefficients β_{1j}, β_{2j}, and β_{3j} are the mean

CBM slope-respective predictor (CBM baseline, writing instruction fidelity, DBI knowledge and skills) slopes plus the unique effect of teacher *j*, and r_{ij} is the student-level residual.

In M3, CBM baseline was a significant predictor of CBM slope (p = .01); for every one-*SD* increase in students' CBM baseline score, CBM slope decreased by 0.27 *SD*. The relation between writing instruction fidelity and CBM slope was not significant. The relation between knowledge and skills and CBM slope was significant (p = .03); for every one-point increase in teachers' pretest knowledge and skills, CBM slope increased by 0.05 *SD*. Teachers' explicit writing orientation and self-efficacy scores were not included in M3, and thus did not explain a portion of the variance in CBM slope.

Discussion

The purpose of this study was to identify whether teacher factors (writing instruction fidelity, DBI knowledge and skills, explicit writing orientation, and self-efficacy) predict students' CBM slope in early writing. Researchers must identify which of these factors are associated with students' progress, as targeting those factors during PD may lead to improved student outcomes. Using HLM to predict CBM slope, we found that a model including teachers' writing instruction fidelity and pretest DBI knowledge and skills resulted in only slight improvement to a model without teacher factors, but was still a possible candidate for best fit. In this model, only student CBM baseline and DBI knowledge and skills were significant predictors. Based on these findings, we conclude that teachers' DBI knowledge and skills may be related to student CBM growth. Additionally, fidelity of writing intervention implementation, at least as it was measured in this study, may be relatively less important than DBI knowledge and skills in influencing student CBM growth.

Teachers' DBI Knowledge and Skills

In our plausible teacher-level model, teachers' understanding of how to implement DBI was related to their students' early writing intervention outcomes. This finding is consistent with the well-established link between teachers' domain and content knowledge and the learning outcomes of student with intensive needs (Cunningham et al., 2004), and is consistent with the findings of Bresina and McMaster (2020). Additionally, this finding provides empirical support for the importance of two aspects of DBI knowledge that have been theoretically linked to student outcomes: CBM graph literacy and DBDM skills (Espin et al., 2018; Fuchs et al., 2012, 2014).

Writing Instruction Fidelity

We did not find that teachers' writing instruction fidelity was related to students' growth. Although this finding is consistent with Bresina and McMaster (2020), it is surprising considering the relation between knowledge and skills and student slope. Logically, teachers' knowledge must be applied in practice to influence student outcomes. Additionally, the lack of relation is inconsistent with previous literature linking instructional fidelity to student outcomes (Durlak & DuPre, 2008), including intensive intervention outcomes (Harn et al., 2013).

There are two potential explanations for this finding. First, we may not have detected an association because our teachers implemented writing instruction at generally high levels of fidelity (range = 79% to 97%; Sanetti et al., 2021), likely due to PD provided in the larger EWP study (McMaster et al., 2020). Durlak and DuPre (2008) proposed that there may be a "threshold" of fidelity (2008, p. 343) beyond which higher levels of fidelity do not lead to further improvement in student outcomes. Our teachers may have been above this threshold of instructional fidelity.

Second, the writing instruction fidelity tool may have not been sensitive to the effect of certain aspects of fidelity. Bresina and McMaster (2020) similarly concluded that the lack of positive relation found between instructional fidelity and student growth may have been due to their measurement of adherence to general instructional behaviors and suggested that including additional dimensions of fidelity may need to be measured to capture a relation. Fidelity is a multidimensional construct (e.g., Sanetti et al., 2021) that necessitates multidimensional measurement. Education researchers measure two dimensions of fidelity: surface and process (Gersten et al., 2005; Harn et al., 2013). *Surface fidelity* measures whether essential components were delivered and time allocation (Durlak & DuPre, 2008; Gersten et al., 2005). *Process fidelity* measures intervention quality and quality of teacher-student interactions (Justice et al., 2008). The process dimension may be more closely related to student outcomes, specifically in literacy (Gersten et al., 2005; Odom et al., 2010). We adjusted the fidelity tool used in Bresina and McMaster's (2020) study to capture both dimensions, but the revised tool might still not have sufficiently distinguished between more and less effective teachers.

DBI Knowledge and Individualized Instruction

Given that DBI knowledge and skills were associated with student outcomes, these factors may have influenced teachers' instructional implementation in a way that was not captured by the writing instruction fidelity tool. Namely, teachers' knowledge of how to make effective data-based decisions could have resulted in more effective individualization of their writing instruction. Modifying prescribed instructional practices to meet specific student needs can lead to better participant outcomes (e.g., Jung et al., 2018). Teachers who know how to effectively use data to individualize instruction could be more likely to affect positive student growth, particularly in the context of intensive intervention (Johnson & McMaster, 2013).

Limitations

Our findings must be interpreted in the context of several limitations. First, we only accounted for one student-level variable in our model, CBM baseline, due to limited sample size. Inclusion of other student variables may have led to different results in our analyses. For example, student grade and gender have been found to be related to CBM-W slope (McMaster et al., 2017). Also, given that teachers determined intervention dosage, there was likely variation in students' writing intervention time. Controlling for this variable may have allowed for a more accurate detection of teacher-level effects. However, student opportunities to respond, an aspect of dosage consistently linked to students' intensive intervention outcomes (Austin et al., 2017; Fuchs et al., 2018; Wanzek et al., 2018), was captured in our writing instruction fidelity tool.

To compare all students' CBM slopes, we combined three CBM measures and two scoring protocols into a standardized outcome variable. Progress monitoring students on different CBM-W measures was necessary in the larger EWP efficacy trial, as teachers selected measures that would be sensitive to their students' growth in order to make instructional decisions. However, ranges of *z*-scores calculated for this study varied across the three measures, which may have introduced additional noise to our models.

Due to limited sample size, we also did not investigate additional teacher-level variables or potential teacher-level interaction effects. Data-based decision-making–related self-efficacy, which predicts teachers' DBDM knowledge and skills and the quality of writing instruction students receive (Oslund et al., 2021; Rietdijk et al., 2018), was not explored. Also, potential interaction effects may have occurred between self-efficacy and explicit writing orientation or writing instruction fidelity, as these factors have been found to be related (Graham et al., 2022; Rietdijk et al., 2018).

Several other limitations should be considered when interpreting the findings of this study. Teachers knew that fidelity observations would occur beforehand, and most observations were conducted in-person. As a result, writing instruction fidelity scores in this study may have been higher than if fidelity was observed without researchers' presence. Also, our DBI knowledge and skills measure had relatively low internal consistency reliability. Future research with larger sample sizes is needed to determine the psychometric soundness of this measure.

Directions for Future Research

Additional research is needed to investigate the relation between teacher instructional beliefs, or explicit writing orientation and self-efficacy, and student outcomes. We did not identify a relation between teachers' beliefs and their students' CBM slope. This finding is not consistent with theory of how teacher characteristics influence writing instruction (Graham et al., 2002; Lembke et al., 2018). The lack of association between CBM slope and teacher self-efficacy may be due to ceiling effects; as a group, teachers' self-efficacy was above average (M = 4.2, SD = 0.54 on a scale of 1–6). However, it is also possible students' response to intensive intervention predicts teachers' instructional beliefs. Students' prior achievement has been found to predict teacher efficacy (Ross et al., 2003). Teachers who observed students' progress in CBM graphs may have been convinced that they were effective at delivering writing instruction, or that explicit instruction was effective. Future research should examine if changes in teachers' beliefs is concurrent with, or results from, their students' CBM growth.

Researchers may also consider refining measures of teachers' DBDM fidelity, as teachers' DBDM may explain the relation between teachers' DBI knowledge and skills and student outcomes found in this study. The DBDM fidelity tool used in the EWP (not included as a predictor in this study) measured DBDM timeliness (whether teacher applied decision rules within a recommended time frame) and appropriateness (whether the teacher correctly selected a decision rule based on visual analysis of students' graphed data). This measure evaluates one aspect of DBDM implementation (timeliness) and one aspect of DBDM skill (appropriateness, or graph comprehension). A future DBDM fidelity measure could consider the quality of instructional changes made (i.e., the level of fit to specific student needs) and the extent to which they are implemented.

However, use of such a DBDM fidelity measure would be difficult for two reasons. First, assessing DBDM quality involves subjectivity, given that students may not be making adequate progress for a variety of reasons. Second, measuring the extent to which teachers implement instructional changes with fidelity may be a significant research undertaking, as it would require instructional observation using fidelity criteria specific to individualized instructional changes. For example, researchers would need to repeatedly observe whether an individual teacher added additional minutes to instruction if that was the teachers' planned strategy to increase dosage. However, examining fidelity of teachers' DBDM in this manner may provide insights into how DBI knowledge and skills influence student progress.

Implications for Professional Development

Increasing the quality of DBI PD that teachers receive may result in increased knowledge and skills and thereby student outcomes. Personnel preparation programs inconsistently train (or do not train) special education teachers to implement DBI (Fuchs et al., 2012; Wagner et al., 2017). As a result, teachers' knowledge and skills related to DBI is often lacking. In a recent study examining teachers' graph literacy, teachers answered only 51% of DBDM-related questions correctly, which may have been due to the limited DBDM-related PD they reported receiving (Oslund et al., 2021). Unfortunately, evidence for the impact of DBI PD on DBI knowledge and skills is mixed. In a meta-analysis of the impact of PD on teacher outcomes related to DBI, Gesel et al. (2021) found a mean effect of $g = 0.57$ ($p < .001$). However, for the outcome of teachers' knowledge and skills, effect sizes ranged from −0.02 to 2.28. This variable impact of PD may be related to the extent to which PD focuses on DBI content knowledge, and the complexity of DBI-related content covered.

There is room for improvement in the content focus of DBI PD. In a review of CBM PD materials, Espin et al. (2021) found a disproportionate focus on collecting CBM data, and little focus on DBDM tasks (e.g., interpreting graphs and linking data to instruction). Although administering and scoring CBM data with fidelity is foundational to DBI implementation, these tasks require relatively fewer cognitive resources in comparison to DBDM, which is the most challenging DBI component for teachers to implement (van den Bosch et al., 2017). PD focused on DBDM is associated with increased teacher DBI knowledge (van den Bosch et al., 2019) and student learning outcomes (van Kuijk et al., 2016).

Data-based instruction PD can also facilitate knowledge and skill development by incorporating ongoing support. Coaching increases teachers' knowledge of intensive intervention concepts (Lemons et al., 2016). Given the complexity of the DBI framework, knowledge and skills related to DBI must be built over time and with practical application. Teachers who must make decisions and adjust instruction in real time benefit from collaboration and problem-solving support through this process to increase student outcomes (Brownell et al., 2017). In addition, coaching involving discussions of student progress results in increased DBI knowledge and skills (McMaster et al., 2020). For teachers to develop deep knowledge of DBI, they must have supported opportunities to practice DBI skills with their own students.

Conclusion

The broadest takeaway from this study is that student progress in DBI likely does not occur in a vacuum—teachers' DBI knowledge and skills seem to be associated with student early writing growth. We did not find a relation between other teacher-level factors, namely, teachers' writing instruction fidelity, and student outcomes. This finding does not necessarily suggest that instructional fidelity does not influence student writing growth; instead, it may indicate that there are dimensions of instructional implementation linked to student growth that were not captured by overall writing instruction fidelity. The association between teachers' DBI knowledge and skills and student CBM slope may be explained by teachers' proficiency at making high-quality instructional changes to meet students' needs. Further research is needed to establish a theory of change between teacher factors and student outcomes in DBI. Most importantly, the effect of DBI knowledge and skills on student CBM slope calls for a renewed investment in increasing teachers' understanding of DBI in PD contexts.

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Supplemental Material

Supplemental material for this article is available on the *Journal of Learning Disabilities* website with the online version of this article.

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