School Level and Other Differences in Illinois Teachers' Use of Data to Inform Instruction

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Using data to inform classroom decision-making is a salient facet of teachers' professional practice. However, some evidence suggests that teacher data use practices are unevenly distributed within and across school contexts. In response, the present study examined school-level (elementary, middle, and high) differences in four categories of data use practices among public school teachers (N=303) from at least 68 schools and 52 districts in Illinois, USA. Concomitantly investigated were differences in data use practices by school locale (city, town, suburban, rural), school socioeconomic status, teacher experience, and teacher primary position. Multiple regression analyses revealed school-level differences for two categories of data use practices, namely using data for ordinary classroom instructional decision making, and using data for programmatic instructional decision making. In both cases, elementary teachers were more likely to use data than middle and high school teachers. Some data use practices also varied as a function school locale, teacher experience, and teacher primary position. Implications for practitioners, researchers, and future directions are discussed.

Introduction

Teachers' reliance on evidence as a basis for classroom decision making—or data-driven decision making (DDDM)—is a salient facet of their professional practice (e.g., Council of Chief State School Officers, 2012; Mandinach & Gummer, 2016; van Geel, Keuning, Visscher, & Fox, 2016). In the context of education, Hamilton et al. (2009) define DDDM as "teachers, principals, and administrators systematically collecting and analyzing various types of data…to guide a range of decisions to help improve the success of students and schools" (p. 46). Teachers and other actors within the education system are not only expected to use student academic data of various kinds (e.g., standardized test data, informal classroom assessment data), but also non-academic data such as class attendance, student demographics, and school climate (Datnow, Park, & Kennedy-Lewis, 2012; Mandinach & Jimerson, 2016; Means, Chen, DeBarger, & Padilla, 2011; Means, Gallagher, & Padilla, 2007).

Expectations in both policy and practice are for teachers to engage in DDDM in a system-wide manner that should benefit teachers and students at all school levels. Indeed, recent evidence confirms that educator data use is a viable strategy for promoting student achievement growth. For example, a two-year school-wide educator data use intervention implemented in the Netherlands was associated with overall student achievement gains that amounted to about a month of schooling (van Geel et al., 2016). Another district-randomized study in the U.S. offered similarly strong evidence for positive effects of a data-driven reform intervention on student mathematics achievement (Carlson, Borman, & Robinson, 2011). While these findings do underscore the potential of data use in education, the impacts of such initiatives are not always positive, consistent, or large in magnitude (e.g., Slavin, Cheung, Holmes, Madden, &

Chamberlain, 2013).

Classroom teachers are key actors in the implementation of data use initiatives. Theoretically, teachers who use data to inform their decisions on instructional goals, methods, time allocation, etc. can better meet their students' needs, resulting in higher levels of achievement (Greenberg & Walsh, 2012; Hamilton et al., 2009; Means, Padilla, DeBarger, & Bakia, 2009; Reeves & Honig, 2015). Despite much interest in data use, though, the analysis, interpretation, and instructional use of data proves challenging for some teachers (e.g., Avramides, Hunter, Oliver, & Luckin, 2014; DeLuca & Bellara, 2013; Sun, Przybylski, & Johnson, 2016). Research suggests that teacher data use practices are unevenly distributed within and across school contexts (Banilower et al., 2013; Farley-Ripple & Buttran, 2014; Goertz, Olah, & Riggan, 2009; Turner & Coburn, 2012), including different school levels (i.e., elementary, middle, and high school; Gallagher, Means, & Padilla, 2008; Hoover & Abrams, 2013; Wayman, Cho, & Johnston, 2007).

The present study revisits previously observed school-level differences in teacher data use practices. Extant scholarship in this area has generally found that data use practices are more common among elementary teachers than among middle and high school teachers, but this body of research features a number of limitations. In particular, prior studies were limited in terms of the scope of the data use practices considered, or the grain size at which data use practices were operationalized. Additionally, many of these prior studies did not account for potentially extraneous variables. These limitations warrant replication studies in different contexts, which consider a broader suite of data use practices and account for other factors relevant to data use.

Specifically, this study examines school-level differences in the distributions of four categories of in-service teacher data use practices: *data use for ordinary classroom instructional decision making* (e.g., lesson planning, instructional modification, next steps); *data use for programmatic instructional decision making* (e.g., acceleration, enrichment, intervention allocation); *data use for communicating in relation to instruction* (e.g., grading, student feedback, and parental/guardian communication); and *data use for understanding student cognition in relation to instruction* (e.g., monitoring student status before and after instruction, and growth/progress, identifying student errors and misconceptions). While understanding school-level differences in data use practices is central, the present study also accounts for four other factors: school locale, school socioeconomic status, teacher experience, and teacher primary position. Increasing the research-based knowledge on differences in teacher data use practices should assist stakeholders, including educational leaders (e.g., district-level administrators) and professional development providers, with designing targets for instructional leadership and teacher education practices, and in general reforming policies and practices aimed at promoting the full breadth of data use practices within the K-12 education system.

Literature Review and Theoretical Framework

What is Data Use?

Data use, or data-driven decision-making (DDDM), has been theorized as a complex, multi-faceted, and cyclical process (e.g., Coburn & Turner, 2011; Hamilton et al., 2009; Mandinach &

Gummer, 2016; Means et al., 2009). Building on earlier work by Marsh (2012), Mandinach and Gummer (2016) characterized data use as a five-phase process:

- The first phase is *identifying problems and framing questions* that are to be addressed with data, based on examination of the school context and consultation with other stakeholders (e.g., educators, students).
- The second phase, *using data*, entails identifying possible sources of data, using technologies to work with data, and analyzing data statistically vis-à-vis a problem or question.
- The third phase is *transforming data into information*, which entails interpreting data and different data displays and representations, examining patterns, and articulating inferences or conclusions.
- Phase four, *transforming information into a decision*, involves specification of actions, such as next instructional steps to take or instructional adjustments to make.
- Finally, the fifth phase, *evaluating outcomes*, entails examining the impact of engagement in the data-use process (e.g., examining changes in student performance after a new instructional strategy was implemented in response to observed data).

Data use by teachers also entails an assortment of knowledge, skills, and dispositions, often termed *data literacy*, which Mandinach and Gummer (2016) defined as “the *ability* [emphasis added] to transform information into actionable instructional knowledge and practices by collecting, analyzing, and interpreting all types of data…to help determine instructional steps” (p. 2).

Given the complexity of data use, the specific data use practices in which teachers can engage are many (Reeves, Summers, & Grove, 2016). Two phases of Mandinach and Gummer’s (2016) data use process model are demonstrably difficult for teachers. Prior research has well documented teachers’ unpreparedness to engage in the process of interpreting data in order to make informed decisions, which is a facet of Mandinach and Gummer’s *transforming data into information* phase. For instance, teachers may struggle in distinguishing different types of data points, and between cross-sectional and longitudinal data (Athanases, Bennett, & Wahleithner, 2013; Means et al., 2011; Pierce, Chick, Watson, Les, & Dalton, 2014; Wayman & Jimerson, 2014). Such interpretational challenges are consequential in that they potentiate invalid inferences and, in turn, incorrect instructional decisions (Dunn, Airola, Lo, & Garrison, 2013).

Mandinach and Gummer’s (2016) *transforming information into a decision* phase, which entails specifying next instructional steps, and instructional strategies to deploy, has also proved to be a particularly elusive aspect of data use. There is evidence that, even among trained teachers who regularly engage with data, data are commonly not used as a basis for action or change. Other sub-processes within this domain include providing feedback to students, selecting students/content on which to focus, identifying performance targets, and deciding how to differentiate or modify instruction and group students. The arduousness of this domain may be explained on account of the fact that it invokes multiple, other forms of knowledge (e.g., content, pedagogy).

How Are Data Use Practices Distributed?

Despite the popularity of teacher data use as a critical component of contemporary systemic education reforms, there is considerable variation in teachers' implementation of such practices—both generally and in terms of specific data use practices (e.g., Banilower et al., 2013; Goertz et al., 2009; Kerr, Marsh, Ikemoto, Darilek, & Barney, 2006). Prior research has shown that the most common data use practices include setting curricular or instructional priorities, modifying instruction for students who are struggling, and determining whether to reteach (Cosner, 2011; Datnow & Hubbard, 2015; Farley-Ripple & Buttram, 2014). At the same time, work suggests that, in general, teachers less commonly use data to identify reasons for poor student performance; identify promising instructional practices; and inform changes to the specific instructional method one has used (beyond just re-teaching the same way with additional support/s; Marsh, Bertrand, & Huguet, 2015; Nelson, Slavit, & Deuel, 2012; Pashler et al., 2007).

School level differences. Just as some educational research has shown school level (i.e., elementary, middle, high) differences in terms of teacher *assessment* and *grading* practices (Brookhart et al., 2016; McMillan, Myran, & Workman, 2002; Ohlsen, 2007; Zhang & Burry-Stock, 2003), there is some evidence for school level differences in *data use* practices. One body of this work focused on teacher use of data from electronic data systems, which are computer-based systems used to facilitate the maintenance, analysis, and interpretation of educational data among educators. Means et al. (2007) found that elementary teachers were more likely to use information from a data system to identify skill gaps and make instructional pacing decisions than middle and high school levels (though the latter difference did not attain statistical significance). Similarly, Gallagher et al. (2008) found that elementary teachers were most likely to use evidence from a data system to pace instruction; and a previous round of the same national survey also showed that elementary teachers were more likely to use results to identify student knowledge/skill gaps. On the other hand, the authors found that elementary teachers were less likely to use data when informing parents of student performance. Gelderblom, Schildkamp, Pieters, and Ehren (2016) even demonstrated differences among teachers serving within the same school level. In their study, grades one and two elementary teachers used information from a data system less frequently than their peers teaching grades three through five.

Other studies not exclusively focused on data systems have identified school-level differences in data use as well. In a large-scale mixed-methods study conducted in Wyoming, Wayman et al. (2007) found that elementary schools featured more data use by teachers relative to middle schools (and especially) high schools. Reeves (2017) also surveyed U.S. student teachers in multiple states and found that student teachers in elementary schools reported significantly more frequent data use practices than student teachers in middle schools; the magnitude of this difference was quite sizable, about two-thirds of a standard deviation. Hoover and Abrams (2013) found that elementary teachers more commonly remediated, retested, or regrouped students based on data than their counterparts serving in middle and high school contexts. On the other hand, in that study middle school teachers were more likely than elementary and high-school teachers to disaggregate benchmark test results by student sub-population.

Reasons for school level differences. School-level difference in data use practices, or other teacher practices for that matter, have many possible explanations. These include factors at both the organizational contextual level/s as well as factors related to teachers working within these different contexts (e.g., Flannery & McGrath, 2017; Young & Kim, 2010). In terms of organization-level factors, different school levels may vary systematically in terms of their organizational cultures related to data and data use (Gerzon, 2015). In the Wyoming mixed-methods study cited earlier, Wayman et al. (2007) indeed found that elementary schools featured a culture more facilitative of data use. School levels also naturally differ in terms of the developmental levels of their student populations. Students at the middle and high school levels might possess a higher capacity for self-regulation, relying less on the teacher for feedback, thus necessitating differential data use practices among their teachers (Brown, Lake, & Matters, 2011; Flannery & McGrath, 2017). Along these lines, there is some evidence that high school teachers feel that if they do their part in teaching the curriculum, any failure to learn should be attributed to students themselves (Ingram, Louis, & Schroeder, 2004). Elementary, middle, and high schools may differ also with respect to the amount and types of data (e.g., state end-of-year tests, interim/benchmark tests) available to teachers (Means et al., 2007), the degree of administrative leadership for data use (Cosner, 2011; Farley-Ripple & Buttran, 2014; Wayman et al., 2007; Sun et al., 2016), and the provision of sufficient time for teachers to use and collaborate around data (Gearhart & Osmundson, 2009; Hamilton et al., 2009; Lachat & Smith, 2005; Wayman & Jimerson, 2013).

Differences in teachers' assessment practices, professional roles, and other characteristics may also fuel differential data-use practices by school level. Firstly, such differences might be observed owing to well-known differences in the frequency and nature of their assessment practices (McMillan, Myran, & Workman, 2002; Ohlsen, 2007; Zhang & Burry-Stock, 2003). For example, elementary teachers more so rely on informal assessment data (Brookhart et al., 2016; Gallagher et al. 2008) and would therefore be less likely to use data from a data system. Data use practices may also relate to teachers' total student load; elementary teachers typically work with a single class of students during the year, whereas secondary teachers often teach multiple sections (but then again, elementary teachers are accountable for the teaching and learning of multiple subjects). Teacher beliefs about assessment and data might also account for school-level differences (Coburn & Turner, 2011; Dunn et al., 2013; Jimerson, 2016; Kerr et al., 2006). In a study conducted in Queensland, Australia, Brown et al. (2011) found that primary teachers were more likely to endorse the belief that "assessment improves teaching and learning" and secondary teachers were more apt to believe that "assessment makes students accountable." Differences by school level may be partly explained on account of differences in elementary and secondary teacher education, which has been linked to instructional uses of assessment data (Zhang & Burry-Stock, 2003).

Other differences. The present study of school-level differences in data use was necessarily non-experimental in nature and employs non-probability sampling. A major impediment the study's provision of strong evidence of school level differences was thusly the fact that such differences may be confounded with other factors at the school- or individual- levels (to the extent that other factors covary with both school level and data use). In light of these concerns, the present study also considered an array of four other factors that have been linked previously to data use, or might plausibly confound simple comparison of teachers in different school levels: 1) school locale, 2) school socioeconomic status (school level),[1] 3) teacher experience, and 4) teacher primary position (individual level). In doing so, the present study not only attempted to rule out the impact of these potentially extraneous variables in drawing comparisons about school level differences, but at the same time explores or re-explores these factors' relations with teacher data use. Brief rationales for these particular covariates are included in this section.

School locale was firstly considered given well-documented differences in human, material, and fiscal resources among suburban, urban, and rural school contexts (e.g., Provasnik et al., 2007). Differential resources—such as the availability of data coaches, data infrastructure, and teacher learning opportunities—might influence school and teacher capacity for data use. The present study secondly considered school socioeconomic status given previously observed differences among higher- and lower-poverty schools in relation to data use. In particular, Means et al. (2007) found that teachers in higher-poverty school contexts used a data system more frequently to track test scores at the grade level, to identify promising practices, and to assess student needs for test preparation.

At the individual level, teacher experience was considered given the fact that this variable has been linked to teacher perceptions of testing (Winkler, 2002), and teacher assessment practices (DeLuca et al., 2016). Evidence on teacher experience's relation to the use of data specifically is mixed; some research has found that more experienced teachers are more likely to use data from a data system to communicate with parents (Means et al., 2007), while some has found no relationship between teacher experience and instructional uses of data (Zhang & Burry-Stock, 2003). Teacher experience may also be a relevant factor in understanding data use because data use as a practice rose to prominence after many current teachers even began their careers.

As the sample comprised classroom teachers and special education teachers, this study also attended to teacher primary position in relation to data use. The underlying principles of data use mirror those of so-called curriculum-based measurement (CBM), a process in which teachers regularly and systematically monitor the progress of students in relation to curricular goals to promote instructional-decision making (e.g., timing, grouping, instructional strategies; Deno, 1985). Given that CBM has long been a practice employed by special education teachers whom work with students with disabilities, such teachers may be more accustomed to data use processes. Similarly, those working in instructional roles but not primarily as a classroom teacher or special education teacher (e.g., instructional coaches) may similarly be better equipped to or more likely to work with data (e.g., in leadership meetings).

The Present Study

The aforementioned literature clearly implies that teacher data use varies by school level. However, the literature cited has a number of limitations for understanding the current school-level distribution of data use practices. First, several of the referenced studies (e.g., Gallagher et

[1] School-level characteristics were considered rather than district-level characteristics because school characteristics are more proximal to teachers' data-use practices.

al., 2008; Means et al., 2007) are now-somewhat dated, having been conducted while educator data use was still gaining steam and as such those findings may no longer apply. Second, several of these studies (Reeves et al., 2016; Wayman et al.) examined school-level differences in teacher data use, in general, rather than in terms of specific categories data use practices. When in other studies school-level differences in specific data uses practices were explored, they were limited with respect to the type of data used (e.g., summative assessment data; Hoover & Abrams, 2003) or the data source (e.g., data systems; Means et al., 2007). Fourth, some studies (e.g., Means et al., 2007) just looked at school level without concurrent consideration of other variables potentially extraneous to the school-level comparison of interest.

Consistent with calls for additional studies on the distribution of data use practices (Hoogland et al., 2016), the present paper endeavored to address the limitations of prior work on school-level differences in data use. In particular, the study investigates school-level differences in four theory-based categories of data use practices: *data use for ordinary classroom instructional decision making*; *data use for programmatic instructional decision making*; *data use for communicating in relation to instruction*; and *data use for understanding student cognition in relation to instruction*. This study relied on data collected in 2015 from public school elementary, middle, and high school teachers in the state of Illinois, and casts a broad net in terms of the types and sources of used data. The study also incorporates several other factors in the same statistical model to rule out alternative explanations for observed school-level differences. In doing so, the present study seeks to not only replicate findings from the literature, but also extend also strengthen the literature on school-level differences in data use practices.

Methods

Participants and Procedures

Participants were 303 public school teachers from at least 68 schools and 52 districts in Illinois, USA who were currently serving in an instructional role.[2] The sampling design was non-probabilistic and entailed two stages. First, using a comprehensive sampling frame, Illinois public school principals were contacted with a request to distribute an electronic survey to their respective schools' teachers via email. Second, willing principals distributed the survey with a sub-set also sending one or more reminder e-mails. As incentives for recruitment assistance and research participation respectively, principals were afforded an aggregate summary of findings pertaining to their respective schools' teachers; and teachers were able to enter into a drawing for one of several small technology prizes. Ultimately, the sample represented teachers from approximately 2% of Illinois public schools and 6% of Illinois public school districts.

Ninety-nine respondents taught in elementary schools (32.7%), 135 taught in middle schools (44.6%), and 69 taught in high schools (22.8%), with all K-12 grades and major secondary subjects (e.g., English/language arts, mathematics, science, social studies) represented in the sample. Per official National Center for Education Statistics categories, 6.2% of participants taught in "city" schools, 8.8% taught in "town" schools, 81.2% taught in "suburban" schools, and 3.8% taught in "rural" schools. The average school proportion of students receiving

[2] School was indeterminable for 19 respondents (6.3%).

free/reduced priced lunch was .33 (*SD* = .26), the average school proportion of Hispanic/Latino students was .17 (*SD* = .17), and the average school proportion of Black students was .09 (*SD* = .18).

The majority of the sample members' primary position was that of classroom teacher (73.3%), with 16.8% serving as special education teachers; smaller percentages served primarily in other roles, such as instructional specialist/coach (2.6%) and English as a Second Language/Bilingual teacher (1.3%). The average age of the sample was 39.68 (*SD* = 11.16). In this study, 78.4% of members of the sample were female, 97.5% of the sample was white, and 2.9% of the sample was Hispanic or Latino.

Findings from a larger project during which these data were collected indicate that the participants generally had completed formal coursework in assessment (less common was coursework in data use/data-driven decision making specifically). In addition, sample members had commonly participated in relevant in-school learning experiences, typically workshops focused on assessment or data use/data-based decision-making (Reeves et al., 2016). The average years of teacher experience for the sample was 13.2 (*SD* = 8.74). Comparison of select sample characteristics with known public teacher population parameters revealed that the sample mean age, mean teacher experience, and percent female were similar to that of the U.S. larger population; however, non-white and Hispanic or Latino teachers were underrepresented within the sample (U.S. Department of Education, 2009, 2013).[3]

Instrumentation

A researcher-developed online survey was designed to measure classroom teacher data use practices as well as to gather information on teacher demographics, professional characteristics, and school contextual characteristics. The survey was administered via Qualtrics (2015) survey software. The survey consisted of 27 items designed to represent specific data use practices codified in professional teaching standards[4] as well as reflected in research and theory on data use (American Educational Research Association [AERA], American Psychological Association [APA], & National Council on Measurement in Education [NCME], 2014). With the purpose of further exploring the difficulties teachers experience in *transforming data into information* and *transforming information into decisions*, the items were written to reflect these practices as framed by Mandinach and Gummer (2016). While the items are not inclusive of every conceivable data use practice in which teachers might engage, they constitute a diverse sample of items related to classroom-level teacher data use practices endorsed in professional teaching standards.

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[3] With the exception of the school level variable, the valid percentages and descriptive statistics (e.g., means, standard deviations) used for sample description purposes are based on the observed data, prior to multiple imputation.

[4] The teacher standards reviewed were: Interstate Teacher Assessment and Support Consortium; National Board Standards; the Classroom Assessment Standards for PreK-12 teachers; Joint Committee on Standards for Educational Evaluation; and Illinois Professional Teaching Standards.

To evaluate the validity of the instrument, exploratory factor analysis (EFA) was used to examine the dimensionality of the 27 items (AERA, APA, & NCME, 2014).[5] A preliminary EFA with an oblique-rotated solution suggested the presence of four inter-correlated and theoretically-plausible latent dimensions. However, in this preliminary model 10 items featured small loadings (e.g., < .5) on any given factor, cross-loadings on multiple factors, and/or impeded meaningful substantive interpretation of the factors. Subsequently, another EFA oblique-rotated model was estimated with these 10 items removed. In this EFA model the Kaiser-Meyer-Olkin measure of sampling adequacy (0.92) was acceptable (Kaiser, 1974), and Barlett's sphericity test was significant, χ^2 (136, N = 303) = 3107.25, $p < .001$, indicating the data were appropriate for factor analysis. A four-factor solution was again indicated via inspection of the scree plot, sums of squared loadings, pattern and structure coefficients, and substantive analysis. Item communalities at extraction ranged from .33 to .88, and sums of squared loadings for the four factors were 6.46 (factor one), 3.59 (factor two), 4.09 (factor three), and 6.24 (factor four).

Table 1 contains pattern (and structure) coefficients for the final oblique-rotated, four-factor EFA model. The first factor featured *six* items and was interpreted to represent *data use for ordinary classroom instructional decision making*, for example, using evidence to: guide lesson plans and instruction modifications, including activities, representations, and materials; and identify next steps, including deciding whether to move forward or reteach. The second factor featured *two* items and was interpreted to represent *data use for programmatic instructional decision making* such as identifying students who need acceleration, enrichment, or interventions. The third factor featured *three* items and was interpreted to represent *data use for communicating in relation to instruction.* This involves grading, and communicating with parents and students about performance. The fourth factor featured *six* items and was interpreted to represent *data use for understanding student cognition in relation to instruction*, for example monitoring students' status before, during, and after instruction; and identifying students' errors, misconceptions, strengths, weaknesses, and patterns in thinking.

All pattern and structure coefficients were larger than .5 for the respective factor, with the exception of one pattern coefficient. The four factors were moderately to strongly correlated, with inter-factor correlations ranging from .43 to .75 (with the largest correlation between factor one and factor four). In light of this evidence for four reliably-measured and distinct dimensions of data use, the four factors were extracted using the regression method and were then used as dependent variables to address the research question about school-level and other differences in data-use practices.

[5] Given negligible amounts of missing data for the 27 data use items (between 0 and 1.3%), mean imputation was used prior to the EFA. While multiple imputation was used for subsequent analyses, a multiple-imputation model with the 27 data use items included was inestimable.

Table 1
Pattern (and Structure) Coefficients for Oblique-Rotated Exploratory Factor Model (N=303)

Item Use data to:	Factor 1	 2	 3	 4
1. Data use for ordinary classroom instructional decision making. α = .91				
Modify instruction or lesson plans for current students.	.95 (.92)			
Identify next steps for instruction.	.71 (.81)			
Modify instruction or lessons plans for future students.	.68 (.75)			
Differentiate instruction.	.66 (.75)			
Select scaffolds to provide.	.61 (.76)			
Identify students for individualized instruction.	.50 (.68)	.38 (.61)		
2. Data use for programmatic instructional decision making. α = .82				
Identify students for acceleration/enrichment.		.82 (.87)		
Identify students for more intensive intervention.		.66 (.76)		
3. Data use for communicating in relation to instruction. α = .74				
Give feedback to students.			.81 (.88)	
Communicate student performance to parents.			.61 (.68)	
Assign grades.			.58 (.57)	
4. Data use for understanding student cognition in relation to instruction. α = .88				
Monitor students' achievement growth/progress over time.				.77 (.77)
Determine students' level of achievement before instruction.				.71 (.74)
Determine students' level of achievement after instruction.				.68 (.79)
Identify student strengths and weaknesses.				.67 (.78)
Identify patterns in student thinking.				.62 (.72)
Identify reasons for poor student performance				.40 (.67)

Notes. Pattern coefficients less than .30 are not shown for interpretational purposes, and structure coefficients (in parentheses) shown only for items with pattern coefficients greater than or equal to .30.

Survey participants were provided with a broad and inclusive definition of the term “data” to increase the validity of collecting data on various types and sources of data—a noted-earlier limitation of some prior studies on school-level differences in teacher data use.

> *Data are pieces of information, and include assessment data (e.g., state or district benchmark test scores, student performance on classroom-based formative and summative assessments such as running records, and student work) as well as other types of data such as student attendance and demographics.*

As dependent variables, the items representing the four data use practices were measured on a 5-point frequency scale: 1 = *Never*, 2 = *Once a month or less*, 3 = *A few times per month*, 4 = *Once a week*, and 5 = *A few times per week*.

To measure differences in data use practices among teachers’ contexts and characteristics, the survey collected information on the respondents’ professional contexts: school level (the primary independent variable), school district, and school. Information on their professional roles and experience (teacher primary position, and years of teaching experience) and basic demographics (age and race/ethnicity) was also collected.

School contextual variables maintained within the Common Core of Data (Keaton, 2014) were also acquired for analysis using unique National Center for Education Statistics school identifiers. These included school level (three levels: elementary, middle, and high) and school locale (four levels: city, town, suburban, and rural). For the purpose of describing the sample and model-based imputation of missing data, the school proportion of students receiving free/reduced priced lunch was gathered (as a measure of school socioeconomic status) along with the school proportion of Hispanic/Latino and Black/African American students.

The scope and nature of missing data was investigated using the SPSS Missing Values Analysis procedure (IBM Corporation, 2016). Missing data was as follows: 6.6% for school locale, 23.4% for teacher primary position, 8.3% for teacher experience, and 6.6% for school proportion of students receiving free or reduced-price lunch (the measure of school socioeconomic status). There were no missing data for the four data use factor scores or the school level variable as school level was both reported by participants and obtained from the Common Core of Data.

Little's (1988) formal test for whether the data were Missing Completely at Random (MCAS) was not significant, $\chi^2(10) = 11.771$, $p = .30$, indicating that the data were MCAS. However, given that listwise deletion would have resulted in the loss of, at least, 23.4% of cases for analysis, multiple stochastic imputation procedures were used to handle missing data via SPSS. Multiple imputation improves the efficiency of estimates, preserves power, and mitigates bias (Allison, 2002; IBM Corporation, 2016; Little & Rubin, 1987). The multiple imputation model comprised the four data use factors, school proportion of Hispanic/Latino students, school proportion Black students, teacher subject taught, teacher race, teacher ethnicity, teacher age, and teacher sex. Constraints were imposed on the multiple imputation procedure in order to prevent the imputation of impossible or implausible values: a minimum of 18 for age, a minimum of 1 for teacher experience, and a minimum of .00 and a maximum of 1.00 for the school proportion of students receiving free or reduced-price lunch.

Analytic Approach

To address whether each of several categories of data use practices relate to school level, as well as other select school and teacher characteristics, the present study employed multiple regression analysis. Four separate analyses were conducted, one for each of the four data use factors (dependent variables). Included in the model as independent variables were school level, school locale, and teacher primary position. These were dummy coded with the reference groups being elementary, suburban, and classroom teacher, respectively. The continuous variables of school proportion of students receiving free/reduced priced lunch and teacher years of experience were also included as covariates. Continuous variables, both independent and dependent, were standardized prior to analysis (M = 0, SD = 1) in order to facilitate interpretation. As multiple imputation was employed to handle missing data, the results of regression analyses with each of five multiple imputed datasets (i.e., regression coefficients, standard errors) were pooled using SPSS. The magnitudes of the regression coefficients were used to examine the practical significance of the results.

The assumptions for multiple regression analysis were met. Although respondents shared contexts (schools and districts), unreported unconditional multilevel models showed non-significant intercept variance in all four data use factors by both school and district (p > .05). Thus, the nesting of respondents within schools and districts did not need to be accounted for in the analysis. Post hoc power analysis, with N = 303 and 9 predictors, revealed that statistical power was very high, .99, for two-tailed detection of a medium-sized, practically-significant fixed effect (f^2 = .15), and was .69 for two-tailed detection of a small-sized effect (f^2 = .02). Tolerance and variance inflation factor (VIF) indices did not suggest collinearity issues (the minimum tolerance was .64 and the maximum VIF was 1.57).

Results

Table 2 contains each of four sets of multiple regression results. The regression model for *data use for ordinary classroom instructional decision making* (factor one) was statistically significant,[6] and explained 14% of the factor variance. Three regressor variables were statistically significant in the model. Teachers in both middle schools and high schools used data for ordinary classroom instructional decision making about .4 of a standard deviation less often than teachers in elementary schools. In addition, special education teachers used data for this general purpose about half a standard deviation more frequently than regular classroom teachers.

With eight percent of the variance explained, the model for *data use for programmatic instructional decision making* (factor two) was also statistically significant. In this model, two variables were significantly associated with the factor while accounting for the other variables in the model. First, teachers in middle schools reported using data for this purpose about a quarter of a standard deviation less often than elementary teachers. Second, teacher experience was related to data use for programmatic instructional decision making with more experienced teachers less likely to use data for this purpose; a one standard deviation increase in teacher

[6] Model ANOVAs based on original rather than pooled data. Regression coefficients and standard errors are based on SPSS pooling of the five multiply imputed datasets.

experience was associated with a .19 of a standard deviation decrease in data use for programmatic instructional decision making.

Table 2
Multiple Regression Analysis Model Results and Coefficients (N=303)

Regressor Variable	Factor 1	Factor 2	Factor 3	Factor 4
School Level				
Middle school	-.41 (.14)**	-.29 (.14)*	.02 (.14)	-.13 (.14)
High school	-.40 (.16)*	-.22 (.16)	.29 (.17)	-.13 (.16)
School Locale				
City	-.01 (.31)	-.14 (.29)	.17 (.31)	.74 (.30)*
Town	-.38 (.23)	-.39 (.21)	-.27 (.22)	-.20 (.21)
Rural	-.24 (.20)	-.11 (.20)	-.25 (.21)	.07 (.20)
Teacher Primary Position				
SPED teacher	.55 (.19)**	.21 (.17)	-.01 (.20)	.49 (.18)**
Other teacher	.09 (.18)	.17 (.19)	-.12 (.19)	.27 (.19)
Teacher experience	-.11 (.06)	-.19 (.06)**	-.05 (.06)	-.07 (.06)
School socioeconomic status	-.07 (.07)	-.03 (.07)	-.06 (.07)	-.09 (.06)
Model *F*	3.47**	1.99*	1.00	2.08*
R^2	.14	.08	.04	.09
R_A^2	.10	.04	.00	.05

Notes. Regression coefficients and standard errors are pooled across the five multiply-imputed datasets by SPSS, and model F, R^2, and R_A^2 based on original data only. Model coefficients for continuous variables are standardized, but unstandardized for dummy variables; the dependent variable was standardized prior to analysis. SPED=special education. Factor 1=data use for ordinary classroom instructional decision making. Factor 2=data use for programmatic instructional decision making. Factor 3=data use for communicating in relation to instruction. Factor 4=data use for understanding student cognition in relation to instruction.
*p<.05. **p<.01. ***p<.001.

The regression model for *data use for communicating in relation to instruction* (factor three) was not statistically significant, nor were any individual predictors in the model. However, the overall model for *data use for understanding student cognition in relation to instruction* (factor four) was statistically significant, with two model predictors found to be statistically significant. Firstly, teachers in city schools were about three-fourths of a standard deviation more likely to use data than teachers in suburban schools. Secondly, special education teachers were more likely than general education classroom teachers to use data to understand student cognition in relation to instruction (by about a half of a standard deviation). The full model for factor four explained nine percent of the variance in the factor.

Discussion

In the current educational accountability era, data are ubiquitous. As key actors in the education system, teachers are increasingly charged with analyzing, interpreting, and using these data to inform their practice and in doing so improve student learning (Athanases et al., 2013;

Mandinach & Gummer, 2016; Schildkamp, Karbautzki, & Vanhoof, 2013). Increasing emphasis on teacher data use notwithstanding, many in-service teachers find such practices challenging (e.g., DeLuca & Bellara, 2013; Means et al., 2009; Sun et al., 2016; Wayman & Jimerson, 2013). At the same time, there is notable variation among teachers within and across school contexts in terms of their data use practices (e.g., Farley-Ripple & Buttram, 2014; Goertz et al., 2009; Kerr et al., 2006). Based on a sample of Illinois, USA public school educators, the present study responded to these challenges by investigating, in depth, five sources of systematic variation in four categories of data use practices.

School Level Differences

Overall, findings indicate some differences between teachers in different school levels in terms of the four considered categories of data use practices. In both cases elementary school teachers used data more often. Teachers in elementary schools were more likely to use data for ordinary classroom instructional decision making than teachers in both middle and high schools. Next, teachers in elementary schools were somewhat more likely to use data for programmatic instructional decision making than middle school teachers. On the other hand, no differences between school levels were observed for using data to communicate in relation to instruction, or using data to understand student cognition in relation to instruction.

These findings are largely consistent with prior research suggesting that elementary teachers engage in data use practices more frequently than their middle and high school counterparts. Gallagher et al. (2008) reported that elementary teachers had been observed to more frequently use student data systems to support decisions about students who possess gaps in understanding and how to pace instruction. The present study correspondingly found that elementary teachers were more likely to use data in similar ways, such as to identify students for individualized instruction and to identify next steps for instruction. While some research has found differences between elementary and secondary teacher assessment and grading processes (Brookhart et al., 2016; McMillan, Myran, & Workman, 2002; Ohlsen, 2007), our findings concerning data use for communicating and understanding student cognition in relation to instruction replicate those of DeLuca et al. (2016) whom did not observe such differences.

While this study's findings comport with some earlier studies, many of those earlier studies are limited for understanding the current school-level distribution of data use practices given that: when they were conducted (e.g., Gallagher et al., 2008; Means et al., 2007); they examined school-level differences in teacher data use, in general, rather than in terms of *specific* data use practices (e.g., Reeves et al., 2016; Wayman et al.); the number of practices represented was limited in number and nature (Gallagher et al.) or limited in relation to the data type or source; and potential extraneous variables were not considered (e.g., Means et al.). The present study's findings, then, provide an updated, nuanced snapshot of school-level differences in a larger suite of data use practices; and are derived from an analysis which accounted for other relevant factors.

Other Differences

This study's data source also afforded some variation by other school (school locale, school socioeconomic status) and teacher (teacher experience, and teacher primary position) characteristics, which were simultaneously investigated in relation to the four categories of data use practices. Relationships with data use practices were observed for three of these four factors. First, special education teachers used data more frequently than classroom teachers for both ordinary classroom instructional decision making and understanding student cognition in relation to instruction.[7] What is notable about these positional differences is that they are rather large. The finding that special education teachers use data more often is perhaps unsurprising given that curriculum-based measurement practices are common among this population (Deno, 1985). Simply put, much of SPED teachers' responsibilities involve assessing students (e.g., diagnostic testing) to make instructional decisions, and data use processes are likely a key component of their ordinary professional routines.

Next, more experienced teachers were slightly less likely than their counterparts to use data for programmatic instructional decision making (e.g., identifying students for more intensive intervention or acceleration/enrichment). This may be the case because more experienced teachers are better equipped to work with students with exceptionalities, as opposed to referring such students to other educators or specialists. Lastly, teachers in city schools were about much more likely to use data than teachers in suburban schools to understand student cognition in relation to instruction. This finding could relate to the increased amount of testing occurring in city schools relative to suburban schools (Lazarin, 2014).

Implications

The present study sought to replicate, update, and extend findings from the literature around sources of systematic variation in teacher data use practices. In doing so, it has implications for researchers studying data-driven decision making (DDDM). For researchers, these findings will reinforce the validity of earlier findings that elementary teachers are more likely to engage in some data use practices. Crucially, this study observed these school-level differences while accounting for other key variables, reducing the plausibility that these observed differences are spurious. In addition to replicating and updating findings from prior literature about school level differences in data use, this study also provides new evidence for the role of other school characteristics (i.e., locale) and teacher characteristics (teacher experience and primary position) in the implementation of DDDM.

The present study's findings also carry important implications for practitioner audiences, such as those in formal and informal instructional leadership roles and professional development providers who desire to promote particular practices (e.g., data use for ordinary classroom instructional decision making, data use for communicating in relation to instruction) among elementary, middle, and high school teachers. School contexts featuring fewer data use practices,

[7] The convergence of this finding about teacher primary position with both theory and prior research should serve to counter concerns that the finding is erroneous owing to a large amount of data having been imputed.

and teacher sub-populations less engaged in such practices, represent critical targets for intervention. For example, in addition to traditional mechanisms of teacher learning such as workshops, there is much recent innovation in methods to promote data use among educators, notably data teams and data coaching. In data teams, educators engage collaboratively in data analysis, interpretation, and use of data within a particular school context (see Schildkamp & Poortman, 2015). With data coaching, local personnel or external consultants work with in-school educators to facilitate DDDM (see March et al., 2015). The finding concerning SPED or less experienced teachers' enhanced data use practice might also suggest that they can indeed be leveraged in data use initiatives. These findings concerning those populations and contexts in which data use practices are relatively limited may also be of value to grantmakers hoping to invest judiciously. In targeting their work, such stakeholders can more strategically work to achieve the aims carved out by recent data use mandates. In turn, systemic improvements to data use practices should enhance the quality of teacher practice, and in doing so, K-12 student achievement.

Limitations and Future Directions

These findings should be interpreted in light of this study's key limitations. In particular, there are limitations related to the data source and methodology. The study's non-probability sampling approach and inclusion of only Illinois, USA teachers may limit generalization to all teachers. Though it bears noting that the sample age, gender, and teacher experience distribution was similar to that of the U.S. public-school teacher population. While the study represented a large number of schools and districts, future work should attempt to replicate further these findings in the context of larger-scale studies that employ probability samples inclusive of more schools, districts, states. Although the available reliability and validity evidence for the instrument's score was favorable, the lack of pretesting and pilot testing with members of the teacher population additionally constitutes a study limitation.

While the present study examined a suite of factors altogether in relation to data use practices, the determinants data use practices are likely various and some factors went unconsidered here (as is evidenced by the relatively small proportions of variance explained). For example, expressly accounting for these teacher educational factors is beyond the scope of the present study, and it is recognized that such factors may constitute a root cause of school-level differences among teachers. Similarly, while prior research has identified some differences in data use based on a teachers' subject-area focus (Hoover & Abrams, 2013; Means et al., 2007; Zhang & Burry-Stock, 2003), the present study did not test subject-area differences given their overlap with school level differences (elementary teachers tend to be generalists, and middle and high school teachers tend to specialize in a specific subject-matter area). These factors as well as others such as class size or teacher load certainly warrant exploration in the future, as either additional correlates of data use (or as mediators of the relationship between school-level and data use practices).

More broadly, while the present study describes differences in the frequencies with which teachers in different school levels engage in some data use practices, it does not pinpoint why such differences exist. As noted, such differences could be due to school-level differences in either organizational contextual factors or individual-level factors (e.g., Young & Kim, 2010).

While generally all teachers are expected to use data, even middle or high school teachers (Datnow et al., 2012), there may indeed legitimate reasons for differences in how specifically teachers in different school levels use data. As was the case in Gallagher et al. (2008), the collection of qualitative data would certainly help further sort out reasons for such differences. Along these lines, future research should attempt to explain school-level differences on account of cultural, structural, and human capital differences among school levels. Identifying potentially-malleable factors related to school-level differences would go far in the way of helping to further promote data use practices that are distributed unevenly across schools. Nevertheless, it is generally necessary to well describe what is happening, as was done here, before phenomena can be fully explicated.

A number of other important questions too still remain. For example, whilst this study cast a broad net in terms of the data used by teachers, given findings concerning elementary-secondary teacher differences in grading practices (McMillan et al., 2002; Ohlsen, 2007) it may also be interesting to examine in more depth the types of data (e.g., informal, classroom-based, or standardized) employed for teacher decision-making at different school levels. Research conducted at the high-school level did show that such teachers rely on diverse data (Datnow et al., 2012).

Conclusion

Data use has been observed to vary widely within and across school and district contexts, making it important to understand systematicities in how such practices are distributed. Toward this end, the present study tested the relationship between five school- and teacher-level characteristics and a set of four data use practices. Findings indicate that teachers in elementary schools, less experienced teachers, teachers in city schools, and special education teachers tended to use data in particular ways more likely (whereas their counterparts tend to use data less often). The findings should help researchers and practitioners better understand the distribution of data use practices in schools so as to inform interventions and further research to increase the implementation of these practices by teachers.

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