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The Effectiveness of Leadership Behaviors in Influencing Data-Driven Decision-Making by Teachers

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The Effectiveness of
Leadership Behaviors in Influencing Data-Driven Decision-Making by Teachers

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Education

by

Nicholas Richard Chitwood

2018

ABSTRACT OF THE DISSERTATION

The Effectiveness of

Leadership Behaviors in Influencing Data-Driven Decision-Making by Teachers

by

Nicholas Richard Chitwood

Doctor of Education

University of California, Los Angeles, 2018

Professor Christina A. Christie, Co-Chair

Professor Mark P Hansen, Co-Chair

This study examined the effect of various district and site level conditions that influence the frequency of teacher data-driven decision-making behaviors. This study is motivated by four research questions: 1) Among various kinds of data available to teachers and principals in making data-driven decisions: a. What is the relative level of availability of that data? b. What is the relative frequency of use of that data? 2) When considering conditions that potentially influence use of evidence at schools, including district office supports, principal leadership behaviors, principal leadership styles, prior training, and attitudes towards data use: a. To what extent do teachers experience these conditions? b. To what extent do principals experience these conditions? 3) To what extent do teachers engage in processes for interpreting evidence at schools? 4) Is there a relationship between types of evidence used by teachers and conditions

influencing use of evidence, and the extent to which teachers engage in processes for interpreting evidence at schools? This study integrates a wide range of qualitative research regarding the role of the district office and principals in implementing key supports and conditions for data-driven decision-making, which are then explored through a principal and teacher survey administered to nine principals and 104 teachers from 11 schools.

The findings from the research revealed that teachers varied in their use of data, as they reported that academic data was both more available and more widely used than non-academic data such as suspension, attendance, or surveys of teachers or parents. In addition, teachers and principals reported varied conditions supporting data-driven decision-making, with principal leadership behaviors reported to occur frequently, as compared with district office supports. Teachers also self-reported very high levels of data-driven decision-making behaviors. Ultimately, this research supported principal leadership behaviors as being the most positively associated with teacher data-driven decision-making behaviors, with district supports having a weak, but positive relationship to teacher behaviors as well. I conclude with recommendations for district and site leaders seeking to improve data-driven decision-making practices in their own organizations.

The dissertation of Nicholas Richard Chitwood is approved.

Robert Cooper

Karen Quartz

Christina A. Christie, Committee Co-Chair

Mark P Hansen, Committee Co-Chair

University of California, Los Angeles

2018

DEDICATION

To Caydence, Paxton, Aria, Bennett…

…and Alissa.

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ACKNOWLEDGEMENTS

When I first came to teach in Southern California, I started looking at master's programs that would lead to my administrative credential, which led me to my first graduate school experience at the University of California, Riverside. I'd like to recognize my cohort from UCR: Anthony, Dan, Teresa, and Tom. Additionally, I'm thankful for the mentorship of Dr. Robert Ream in influencing so much of my thinking about education that has impacted both my day-to-day work in schools as well as my doctoral studies at UCLA.

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Thank you to Cohort 22 for the being the type of cohort that needed to hear a good "Shhh…." every once in a while.

I am also indebted to the districts, schools, teachers, and principals who took time to respond to my survey. I am keenly aware of the many things coming through your email on a daily basis, and I appreciate you having made this study a priority.

Finally, I am thankful to God for the many blessings in my life, including a wonderful family here on this earth. He has also given me a strong curiosity regarding how the world works, and the passion to utilized what I've learned in service of public education. I hope I can make a difference for those kids who need it the most.

> *"Truly, I say to you, whatever you did for one of the least of these brothers and sisters of mine, you did for me." Matthew 25:40*

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CHAPTER 1: INTRODUCTION

Policy makers have come to rely upon *data-driven decision-making* in schools as an essential component of school reform. This broad term generally refers to the use of student data for educational decision making in many areas, including but not limited to curriculum and pedagogy, as well as in the allocation of resources. While federal and state policy instruments contribute to the expansion of the use of data in the instructional setting, there is only a limited set of research on how educators respond to and interpret these data, whether at the teacher level (Marsh & Farrell, 2015), or at a larger district-wide level (Cho & Wayman, 2014). The existing research has implications for understanding policy implementation regarding the use of student data, but there remains a key gap in researchers' understanding of data use by educators - the influence of school leadership on teacher data practices. Prescriptive lists of steps for leaders to take in performing leadership on data practices are readily available (Noyce, Perda, & Traver, 2000; Reeves, 2008), and many researchers have performed qualitative localized studies of data-driven leadership (Anderson, Leithwood, & Strauss, 2010; Datnow, Datnow, & Park, 2014; Halverson, Grigg, & Prichett, 2007; Levin & Datnow, 2012; Liou, Grigg, & Halverson, 2014; Marsh & Farrell, 2015; Park & Datnow, 2009). However, another gap remains in looking at site leadership practices quantitatively across a district, as embedded within schools, and the teacher experience. To this end, the present study will examine teacher behaviors and practices in data-driven decision-making, and the possible contributions of leadership behaviors by principals and district offices in promoting those behaviors.

Responding to student achievement data has been a key process in education for many years. However, a focus on student data was reinforced by the adoption of the No Child Left Behind (NCLB) act in 2001, in which student data were required to be disaggregated by ethnicity, poverty, as well as language proficiency. This legislation had the net effect of drawing greater attention to differing student needs and outcomes (Rudalevige, 2003). This very act of requiring the reporting of subgroup data was the first step forward in drawing attention to inequities in student outcomes, inequities which had been well known and well-studied to this point (see Jencks & Phillips, 2011) for an overview of the achievement gap). However, these inequities had not yet reached the public consciousness. NCLB was not just the catalyst sparking greater attention to student data, but it also represented a shift in the way in which schools, and ultimately districts, were held accountable for student achievement results. Since the adoption of NCLB, schools and districts not meeting benchmarks for achievement found themselves in an increasingly punitive set of sanctions known as *Program Improvement* (PI). These sanctions ranged from the creation of improvement plans at the site level, all the way to dismissal of the principal and half of the teacher staff at the site and filling in the staffing with new hires. These increasingly onerous sanctions created an education environment in which educators had strong incentives to make instructional decisions centered around achievement results, especially those that could possibly cost them their jobs.

Schools and districts struggled to respond to the requirements imposed by NCLB for a decade and a half. Indeed, this focus on student data showed no sign of diminishing as the nation transitioned to the Common Core educational standards. Given this transition, however, the California Smarter Balanced Assessment in its initial year of implementation had lower proficiency rates as compared to the tests under the old assessment system known as the California Standards Tests (Leal, 2015). These lower proficiency rates provided a challenge for educators. Additionally, the outgoing Obama administration also pushed the use of achievement tests—such as those provided by the Smarter Balanced Assessment Consortium— for noninstructional purposes, such as teacher evaluation and through the Race to the Top series of grants to states in 2009 (The White House Office of the Press Secretary, 2009). With the signing of the Every Student Succeeds Act (ESSA) in December of 2015 by President Obama, which overhauled many provisions of No Child Left Behind, there became an opportunity for states to rethink the punitive system of accountability that existed at that time. While the financial effects of Race to the Top have faded in the context of the adoption of ESSA, as well as the change in administrations, the possible model of using student data for teacher evaluation persists. It is in this context of high stakes accountability, changes in achievement tests, and increasing use of data outside of instruction, that successful implementation of data-driven decision-making processes continues to gain relevance.

This transitional moment provides a unique window in which one can study the process of data-driven decision-making. Districts had over a decade with the old standards-based tests, the California State Tests (CSTs). Consequently, some patterns of responding to data evolved, including a focus by districts on students scoring near proficiency, known as “bubble kids”. Since these students created movement in accountability results, much more easily than those far below proficiency, districts prioritized their learning. However, even in the face of such strategies, achievement gaps persist. In this moment of change, stakeholders at all levels are struggling to adjust instruction and instructional decision-making to the new Common Core standards, the new achievement tests to measure those standards, and the new ways in which districts are held accountable. By Fall of 2017, Districts have received three years of data regarding student achievement, and a significant process of meaning-making has occurred as a fourth year of assessments are underway. This provides a context in which to study the data leadership practices of site leaders and their impact on teacher practice.

In addition, the new accountability framework being developed by the State of California has broadened the types of data for which districts will be accountable. In 2017, a new public facing California School Dashboard made its debut (Tira, 2017). This dashboard featured more than just academic achievement data, as attendance, suspensions, and English learner language acquisition data also were present and had equal impact on districts as far as identification by the State for technical assistance, or eventually intensive support, a status which has yet to be well defined. Understanding data practices across a variety of data types will provide a baseline by which to understand how teachers operate within this new accountability system.

Theoretical Framework

The theoretical framework guiding this research was derived from Anderson et al. (2010). Anderson et al. describe the framework as follows:

> In this framework (Figure 1), student learning is the dependent variable, influenced most directly by the decisions and actions of school principals and their staffs. Types of evidence available to the school and existing conditions influencing how evidence are interpreted and used are variables shaping the processes for interpreting evidence used by principals and their colleagues in their decisions and actions.

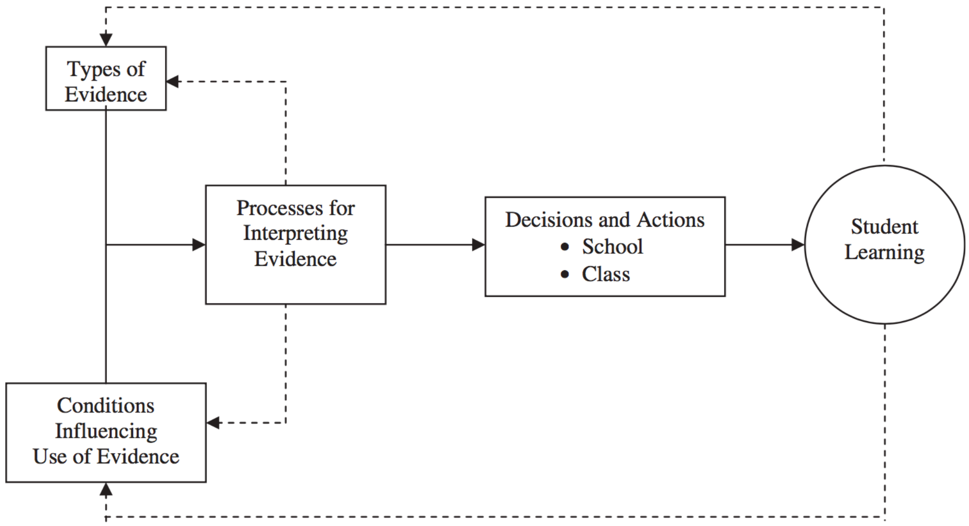

Figure 1. Framework for understanding evidence-informed processes

My interpretation of Anderson's framework as seen in Figure 2 is intended to focus on a few key parts: the *types of evidence* used by decision-makers, including the evidence types, as well as the availability of that evidence; the *conditions influencing the use of evidence*, as measured through district office supports, principal leadership behaviors, principal leadership styles, prior training, and attitudes towards data use; and the extent to which educators engage in *processes for interpreting evidence*. The actual decisions made by educators, as well as the student outcomes in Anderson's framework are outside of the scope of this study, and therefore my framework.

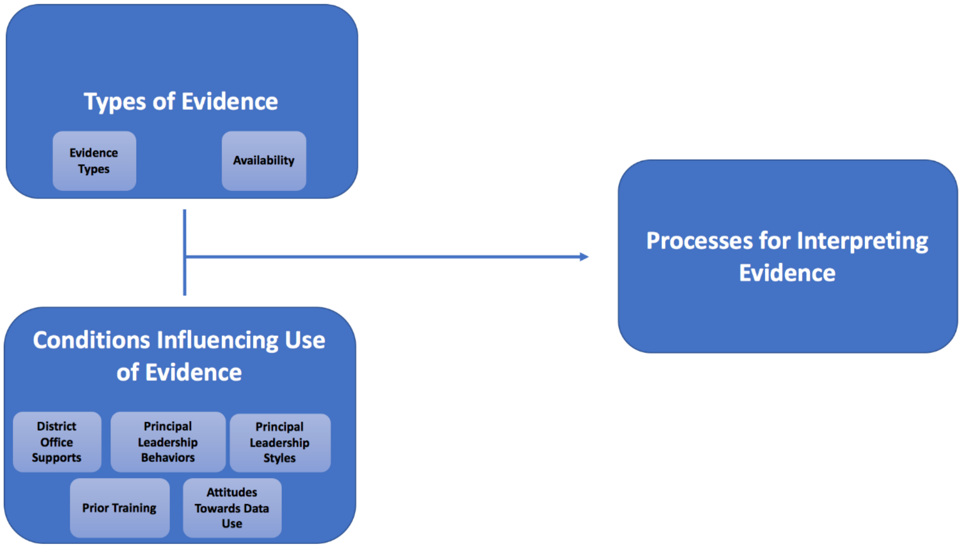

Figure 2. Summary of framework for study

As we take a closer look at the framework, the types of evidence that will be surveyed among teachers are as described in Figure 3. These types of evidence were added to the theoretical framework due to their presence in the discussion of research on data-driven decision-making by Marsh et al. (2006), as well as Datnow and Park (2014).

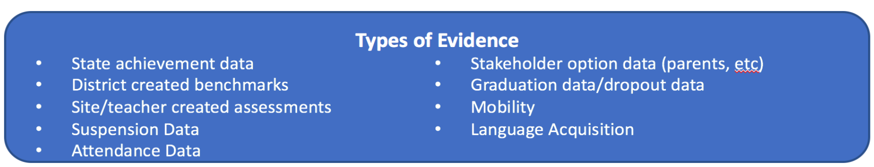

Figure 3. Types of evidence in the study

There are five categories of conditions that influence the use of evidence included in the theoretical framework for the study as show in Figure 4. When considering the district promotion of data-driven decision-making, research by Anderson et al. (2010) identified the specific district leadership practices that influenced teacher practice. The principal behaviors in the framework were delineated by Marsh and Farell (2015). Leadership style was explored by Park and Datnow (Park & Datnow, 2009) and Liou, Grigg, and Halverson (2014), who had contrasting findings regarding the effectiveness of prescriptive versus distributed leadership, which I explored in this study. Coburn and Turner (2011) described the important role that beliefs played in data use, resulting in the inclusion of attitudes regarding data-driven decision-making in the study. Finally, Earl and Katz (2006) emphasized the varying levels of comfort with data use as a factor in use of data. Therefore, I included levels of preparation to undertake data-driven decision-making, as well as previous training settings as part of the framework.

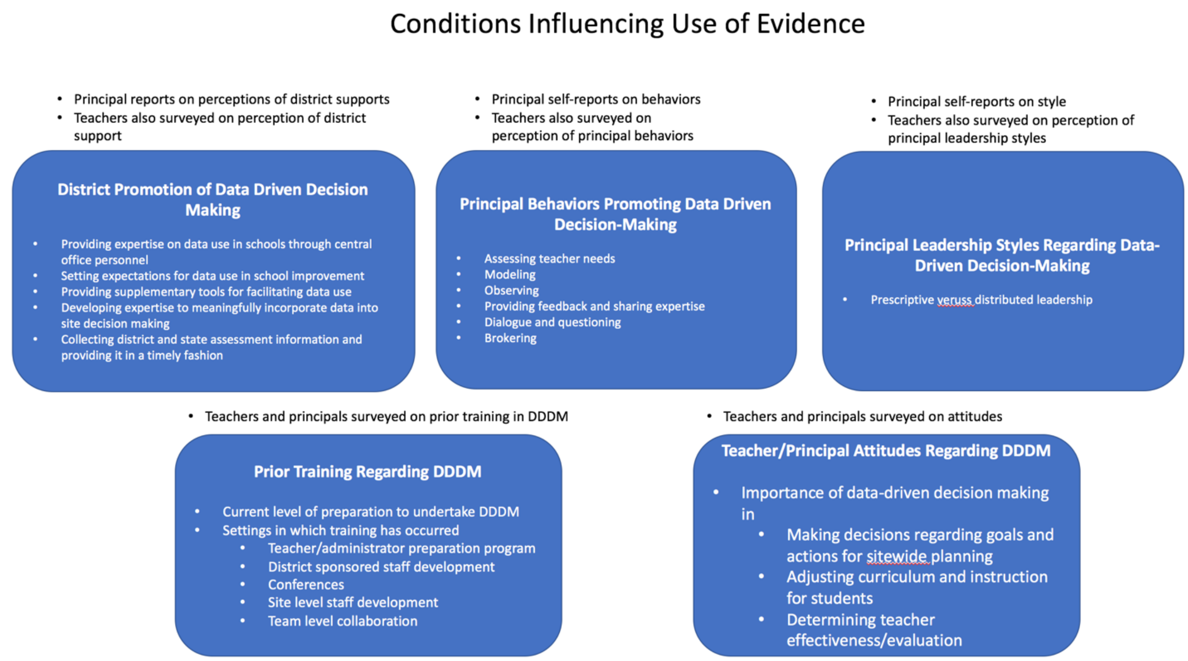

Figure 4. Conditions influencing the use of evidence in the study

Finally, Figure 5 details the teacher processes for interpreting evidence that this study was interested in, which were derived from Marsh et al(2006).

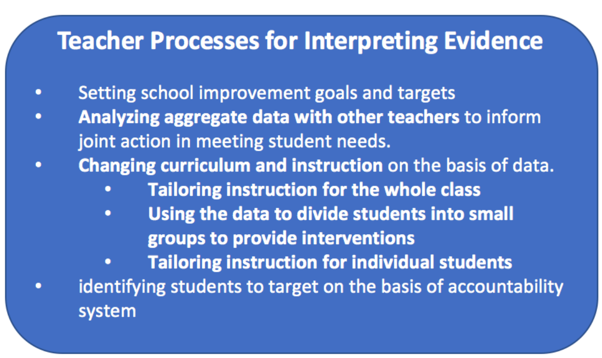

Figure 5. Teacher processes for interpreting evidence

Research Questions

In order to address the gap regarding the process of data-driven decision making as it relates to school and district leadership, the following research questions guided my study:

1) Among various kinds of data available to teachers and principals in making data-driven decisions:
    a. What is the **relative level of availability of that data**?
    b. What is the **relative frequency of use of that data?**
2) When considering conditions that potentially influence use of evidence at schools, including district office supports, principal leadership behaviors, principal leadership styles, prior training, and attitudes towards data use:
    a. To what extent **do teachers experience these conditions**?
    b. To what extent **do principals experience these conditions**?

3) To what extent do teachers engage in processes for interpreting evidence at schools?

4) Is there a relationship between types of evidence used by teachers and conditions influencing use of evidence, and the extent to which teachers engage in processes for interpreting evidence at schools?

CHAPTER 2: LITERATURE REVIEW

Policy makers have come to rely upon data-driven decision-making in schools as an essential component of school reform. When President Bush sought to counter the “soft bigotry of low expectations” through the passage of No Child Left Behind, the policy instrument of choice was not an additional infusion of federal funds beyond the existing programs in place, but instead a stronger system of school and district accountability. Policy makers came to believe that low expectations were enabled by test score data that hid differences in achievement among minorities or low-income students through an aggregation of results among all students on a campus. Instead, through disaggregation, achievement results were reported for all sub-groups, and if even one subgroup were missed achievement targets, a school would fail to meet Adequate Yearly Progress. The natural consequence of this policy attention to achievement results was that educators increased their reliance on student data and this drove educational decision-making.

In order to place data-driven decision-making in context, I first discuss the achievement gap which has motivated a large portion of the discussion about the direction of K-12 education. Next, I examine the evolution of accountability policies, such as No Child Left Behind, in promoting data use as a response to the achievement gap. After discussing accountability policies, I then discuss the literature on data-driven decision-making through the lens of the framework detailed in Chapter 1, with an emphasis on the types of evidence used, teacher processes for interpreting evidence, and finally the conditions influencing the use of evidence. The review concludes with an emphasis on leadership and its particular influence on data-driven decision-making.

The Achievement Gap

Attention to the differing opportunities afforded to students based upon race can be traced back over 60 years to the case of Brown v. Board of Education. In this case, the Supreme Court attempted to address inequality by disallowing explicit segregation of students; however, funding disparities remained between majority black urban schools and white schools. These unequal opportunities were demonstrated most vividly by the resulting gap in achievement outcomes, known as the "achievement gap". Coleman (1966), in his landmark Equality of Educational Opportunity report, found that only the top 15% of African-American students fell in the same academic performance band as the top 50% of white students. In 1971, National Assessment of Educational Progress (NAEP) results revealed a black-white reading gap of 1.21 standard deviations, and a math gap of 1.33 standard deviations (Jencks & Phillips, 2011). As of the 2007 National Assessment of Education Progress, average eighth grade reading and mathematics scores continued to indicate a gap between white students, and both Hispanic and black students (Barton & Coley, 2009). On the NAEP reading test, for example, the average reading score among white students was 272, while Hispanic students received a 247, and black students scored at an average of 245. On the NAEP mathematics tests, the average score for white students was a 291, while Hispanics received an average score of 265, and black students received an average score of a 260. Measurable gaps in achievement were present before school even began (Alexander, Entwisle, & Olson, 2016), and widened over the course of public schooling, and interestingly enough, the gap was shown to decrease slightly during the school year and widen over summers.

Closely related to the conversation about gaps in performance due to race, were gaps in performance tied to social class differences. Rothstein (2004) pointed out that the Coleman report concluded that variation in school resources could not account for most of the variation in test scores on average. Instead, family backgrounds, as well as different social and economic conditions accounted for two-thirds of the difference in achievement. One of the possible causes identified by Rothstein for the gap was genetic influence. However, these genetic differences were likely distributed identically across races, precluding a genetic theory of racial achievement differences. Next, social class differences in child rearing were considered. One example of such a social class difference was present in the study by Hart & Risley (2003) as researchers found a word gap between children in poverty and middle-class households by age 3. Greenwood & Hickman (1991) point toward numerous positive outcomes for students associated with increased parental involvement, including higher achievement, student sense of well-being, student school attendance, positive student attitudes and behavior, and student readiness to do homework, among other outcomes. However, families in poverty may not know how to confront a school system when necessary to advocate for the well-being of their students.

Given the scope of out of school factors, one possible conclusion might be that schools cannot make a difference in closing the gap. However, there still remains a significant variation in achievement that can be traced back to the school system, and it was this in-school variation that was targeted through data-driven decision-making. In their policy brief, Barton and Coley (2009) referenced many factors reflecting school level dynamics, such as curriculum rigor, teacher preparation, teacher experience, teacher absence and turnover, and class size. In this study, rigor of the curriculum referred to the level of classes in which students were enrolled. On a positive note, Barton and Coley (2009) noted that African-American students have closed the gap as of 2005 in attaining a mid-level curriculum. A mid-level curriculum was defined as at least four years in English and three each in social studies, mathematics, and science, plus completion of geometry and algebra II, at least two courses in biology, chemistry, and physics, and at least one credit in a foreign language. However, Hispanic students had not closed the attainment gap. In addition, substantial gaps in Advanced Placement Test performance remain, with 63% of White students scoring a 3.0 or better, while 47% of Hispanics scored at a 3.0 or better, and only 29% of African-American students meeting that benchmark. This shows that enrollment in the right classes is not enough to address disparities in outcomes.

Accountability Policies

Persistent achievement gaps, along with Coleman's findings, provided the backdrop for the passage of the Elementary and Secondary Education Act during the Johnson administration in 1965 (Spring, 2013). Through ESEA, as reauthorized over the years as the No Child Left Behind and Every Student Succeeds Act, the federal government provided additional financial resources to local districts and states in an attempt to address the achievement gap. However, addressing unequal funding was not the only concern for policy makers regarding education during this period. The launch of Sputnik in 1957 marked a dramatic moment for the American people. Suddenly, the quality of the American education system was questioned as the Soviet system had surpassed our own as the Space Race kicked off (Kirst, 2010). While the equity-focused reforms exemplified by ESEA persisted throughout the 60s and 70s, in the 80s, a differing policy focus emerged that was focused on high quality education standards. The standards movement started to gain traction as globalization created additional pressures on the education system to prepare students for the workforce. The economy had shifted in the twentieth-century from a manufacturing focus towards knowledge-based work (Drucker, 1994), increasing the pressure on K-12 education to produce well-educated workers ready for a global economy. These two threads, of equity and globalization came together in the 2001 with the passage of No Child Left Behind.

No Child Left Behind and Its Key Components

No Child Left Behind was passed by Congress and signed into law in 2001 (Rich & Lewin, 2015). The law was a major reform of the role of the federal government and reflected an increased emphasis on high-stakes accountability as compared to the original incarnation of the law, the Elementary and Secondary Education (ESEA) Act signed in 1965 by President Johnson. Originally due for reauthorization in 2006, No Child Left Behind languished for almost another ten years in an political environment in which the sort of major compromises that enabled its passage in 2001 had been out of reach until its sudden reauthorization at the end of the 2015 (see Rudalevige, 2003). By the turn of the century, federal policy makers did not see simply providing additional resources to equalize school inputs as being a sufficient policy mechanism by which to address the achievement gap (Rudalevige, 2003). In addition, researchers such as Hanushek (2003) had over time been calling into question the very assumption that increased financial resources made a difference in educational outcomes. The solution in No Child Left Behind: a two-pronged approach with high-stakes accountability based upon standards-aligned assessments, as well as strong sanctions for schools in cases in which the school failed to make progress towards proficiency for all students at the school site.

The accountability provisions of No Child Left Behind required regular assessment of students in third through eighth grade, as well as one time in high school. All states were required to adopt content standards and achievement standards to define proficiency. In addition, true to its name, No Child Left Behind set a goal for all students in the country to be proficient by 2014 (Ravitch, 2013). In the meantime, to address what George W. Bush termed "the soft bigotry of low expectations" (Rudalevige, 2003), student achievement results on an ongoing basis were required to be disaggregated by numerically significant subgroups, such as English learners, students with disabilities, or by ethnicity (Kirst, 2010). Previously, aggregated results for a school could mask subgroup underachievement if other subgroups did well. If schools did not meet proficiency standards for all subgroups, then they were subject to sanctions termed “Program Improvement”. These sanctions ranged from the creation of improvement plans at the site level, all the way to dismissal of the principal and half of the teacher staff at the site and filling in staffing with new hires. While the goals of the legislation were admirable, it was not clear whether the assessments that were developed actually aligned completely with the content standards they were supposed to be assessing (Polikoff, Porter, & Smithson, 2011), and undermined their credibility as an accountability tool.

Consequences of No Child Left Behind

While research has shown that the implementation of high-stakes accountability provisions in No Child Left Behind was inconsistent, there still were consequences for the K-12 public school system in the United States. Meier (2002) detailed some of these consequences, including an increased dropout rate since the adoption of NCLB, and a narrowing of curriculum away from arts and other non-tested subjects. Ravitch (2011) noted that the transfer provisions and tutoring services were not utilized by many students. In addition, high-stakes accountability was extended from schools to individual teachers as a natural extension of the No Child Left Behind accountability philosophy in recent years. Hanushek’s (2003) work found that changing financial inputs to the school system was not effective, and claimed that incentivizing teacher production of student outcomes was the next step. Value-added measures in which teachers are evaluated on the growth of their students, instead of the overall rate of student success, have increasingly been considered as elements for teacher evaluation as well as a possible basis for pay based upon merit. However, there remain several reasons for concern about this extension of high stakes accountability.

One aspect of Hanushek's findings was that traditional criteria by which teachers' compensation was determined, such as experience or level of education, did not make a difference in student outcomes. However, other researchers have found the opposite, and noted a trend in which less experienced teachers tend to be placed at more urban and ethnically diverse schools. These less experienced teachers were found to contribute towards the achievement gap (Barton & Coley, 2009). In addition, value-added metrics were unstable and had poor correlation when different assessments were applied to the same teacher, such as California State Standards Tests versus SAT scores (Papay, 2011). Finally, research has proved ambiguous as to how value-added measures had correlated with existing evaluation procedures to provide an accurate picture of teacher quality (Harris, Ingle, & Rutledge, 2014).

Even more troubling, some researchers have found that NCLB and its accountability provisions may have actually stalled progress on closing the achievement gap. Fuller et al. (2007) found that fourth graders continued to close the achievement gap in the 2005 NAEP administration, but the gap was closing at a slower rate than prior to the adoption of NCLB. Some states did show gains in the proficiency rate for the period studied on their own assessments, but these results were possibly tainted by the ability of states to determine their own definitions of proficiency. By redefining proficiency multiple times over the course of implementation of the policy, some trend lines were caused to be uneven and jagged, making understanding the true growth (or losses) that students were experiencing difficult to measure accurately. In contrast to the negative findings by Fuller et al., however, Lauen and Gaddis (2012) found that while NCLB failed to decrease the achievement gap for all subgroups, schools responded to failing AYP with boosts in performance the following year for those failing subgroups.

Ultimately, No Child Left Behind was a noble attempt to address both the unequal outcomes for students of color in US schools, as well as to address the larger global context in which US students are expected to compete. However, the move towards stricter testing and harsh accountability sanctions did not convincingly improve outcomes for all students, especially when taken in consideration of the stated goal of 100% proficiency for all students. Through the reauthorization of No Child Left Behind under the Every Student Succeeds Act, some of these failings of No Child Left Behind have been addressed.

The Every Student Succeeds Act and the Future

As of the writing of this review, there is ambiguity about the ways in which the Every Student Succeeds Act will impact districts and schools as they continue to address the achievement gap. Some of the most punitive elements of No Child Left Behind have been removed, such as the requirement for all students to demonstrate 100% proficiency, as well as the punitive sanctions imposed on schools and districts through Program Improvement. Instead, accountability consequences and sanctions have become the responsibility of individual states. The definition of proficiency is up to states, as well as the circumstances under which to impose sanctions, and California recently submitted to the Federal government its plan to meet ESSA requirements (Resmovits, 2017).

The requirement to test students remains in grades 3-8 and once in high school. The frequency of testing, and the fact that local accountability will still derive from the results of these tests makes it unclear how districts and schools will adapt to the new system. Under No Child Left Behind, the strong accountability regime created an environment in which schools and districts had to develop processes in which to respond to the potential punishments. One such process has come to be known as *data-driven decision-making*, in which student data is used in a cycle of continuous adaptation and improvement of educational decision-making. While there has been some loosening of the accountability environment, it seems likely that schools will continue to implement data-driven decision-making in response to the still regular standardized testing that students will be expected to complete, especially as the types of data used in accountability expands beyond just achievement data.

Data-Driven Decision-Making

As both incentives and consequences regarding the use of data in the instructional setting continue, there has been a limited amount of research on how educators respond to and interpret these data. Historically, researchers have proposed multiple models of data use. One commonly cited model of data use focusing on individuals using and processing data was proposed by Mandinach et al. (2006), as seen in Figure 6. In their conceptualization, the individual data has to go through multiple stages in the process of meaning making, including analysis and summarization prior to becoming useful for practitioners. Mandinach et al.'s framework is also important in that it shows these processes as being embedded within a classroom, building, and district context, corresponding to the differing levels of the hierarchy examined in my study.

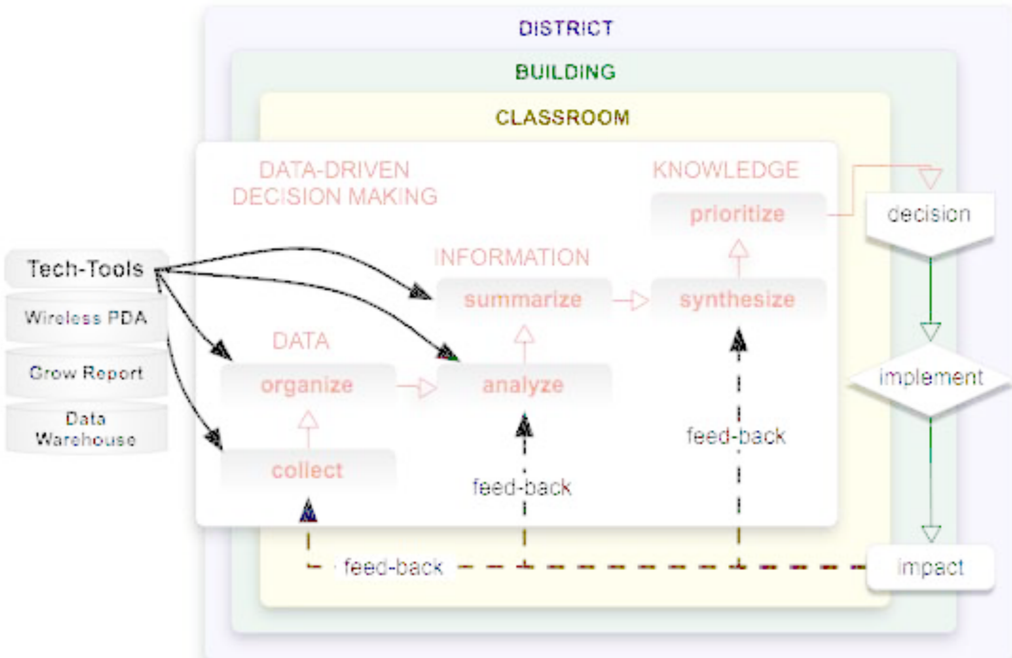

Figure 6. Mandinach et al.'s Model of Data-Driven Decision-Making

Mandianch's model then influenced Ikemoto and Marsh (2007), in which the authors attempted to understand how educators made meaning regarding data-driven decision-making. Using survey and interview data from two studies they had undertaken, they reinterpreted the data in order to develop their framework, seen below in Figure 7.

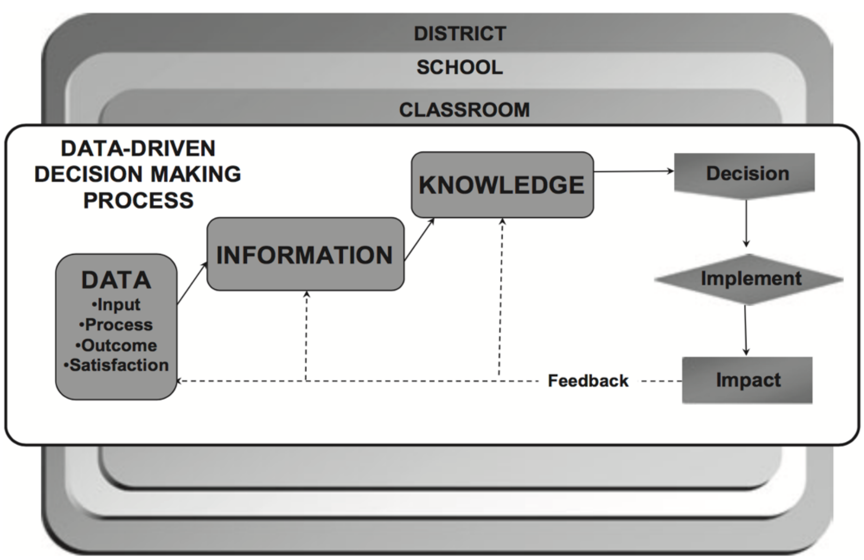

Figure 7. Ikemoto and Marsh Framework for Data-Driven Decision-Making

Ikemoto and Marsh's work in turn impacted Anderson et al. (2010), ultimately resulting in the framework in Figure 8 which has driven discussion on the foundations of data-driven decision-making among other researchers (Datnow et al., 2014). Direct influence relationships are indicated by the solid lines in the framework. In addition, the authors also acknowledge the possibility of parts of the framework to work backwards in influencing the model as indicated by the dashed lines. For example, a possible outcome of the process of interpreting evidence may not be actions in the classroom, but instead could be discovering the need to identify new types of evidence. Also, student learning will then provide the types of data to continue to cycle of data-driven decision making. This framework was used by the authors to conduct a mixed-methods study of how leadership influences student learning.

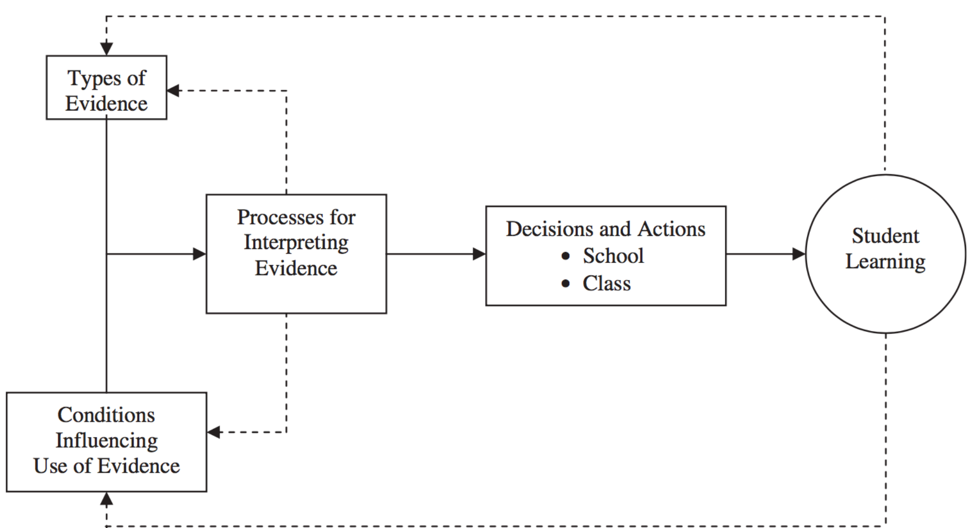

Figure 8. Framework for understanding evidence-informed processes

The simplicity of this framework informs three key questions for this review: What types of data are used, how is data used, and what support is there for data use? For the sake of consistency, these ideas will be considered through the language of this study's framework: which types of evidence are used, what processes are there for interpreting evidence, and, finally, what conditions influence the use of evidence?

Which types of evidence are used?

Marsh et al. (2006) note that state tests are one of the most popular forms of outcome data, an observation supported by Anderson et al. (2010). These researchers also mention district developed benchmark tests, as well as classroom tests or homework, as important and more timely sources of data, as practitioners felt that achievement test data was not timely enough for decision making. Emphasizing the importance of interim assessment data, one of the first national experimental studies on data-driven decision-making was designed around benchmark assessments (Carlson, Borman, & Robinson, 2011). Marsh et al., along with Datnow and Park (2014), also note that many non-achievement student outcomes are also used: attendance, mobility, graduation rates, and dropout data, for example. In contrast, process data regarding classroom pedagogy was less frequently used for decision-making. Finally, one last type of data used is opinion and satisfaction data from a variety of stakeholders, including parents or other members of the community. Coburn and Turner (2011) also emphasize that the availability of data has implications for how data routines unfold. Organizations emphasize and collect some types of data and not others. People have different levels of access to data, and data is sometimes available on different time scales; some data is available immediately, some not until much later.

What processes are there for interpreting evidence?

Having addressed the types of data used, Marsh et al. (2006) explored how administrators and teachers use the data. One primary use of data is towards **setting school improvement goals and targets** as part of the cycle of school planning, reinforced by Levin and Datnow (2012). However, this use of data had the potential to be identified as being compliance driven, rather than meaningful. Another rational, but potentially harmful, use of data corroborated by Datnow and Park (2014) was that of **identifying "bubble kids"**. These students are close to the proficiency level needed to meet accountability targets, and were able to provide the largest possible gains for a given amount of instructional effort on high-stakes testing as envisioned under No Child Left Behind. Datnow and Park note that little effort was expended on ways to move students from proficient to advanced.

Another important use of data is **changing curriculum and instruction** on the basis of data. This could appear in three distinct forms, moving from whole class impacts to individual impacts: **tailoring instruction for the whole class** based upon group results, **using the data to divide students into small groups** to provide interventions for those small groups, or **tailoring instruction for individual students** (Marsh et al., 2006). However, it was found that it was much less likely to see student level use of data by teachers than whole class use. Zooming out another level, one other important use of data centers on **analyzing aggregate data with other teachers** to inform joint action in meeting student needs.

Marsh et al. also find that data **did not** tend to be used in high stakes decisions regarding students or teachers, though exceptions of course existed, including English learner reclassification, for example. On a side note, if studied now, a decade later, this finding might look quite different due to the varying incentives provided by the Department of Education under Arne Duncan under the waiver era of No Child Left Behind in 2011-2015. In this more recent era of waivers, accountability provisions of NCLB were waived for states who were willing to commit to some level of teaching evaluations based upon student achievement results, possibly contributing to a growth in using student data to make high stakes decisions, at least in the area of personnel, effects that still be visible even with the adoption and implementation of ESSA

What conditions influence the use of evidence?

Marsh et al. (2006) also consider the kinds of conditions of support for evidence use.

While professional development was available, most administrators and teachers did not find it to be useful. In addition, technology systems were also reported to be available as a support, but not commonly used at the time of the Marsh et al.'s study, nor of major importance. This finding regarding access to computer data system is corroborated by Cho and Wayman (Cho & Wayman, 2014). They find that the availability of computer data systems did not result in a change in data use practice among teachers. In fact, the process of meaning-making for teachers regarding student data drove the rate of use of the systems, rather than the systems providing new or improved opportunities for teachers to engage with student data. Additionally, the district office could be of assistance in helping to shape the meaning that teachers generated about student data, but tended to focus instead on technology and logistical issues. This sometimes caused teachers to be frustrated regarding the process of data use who were looking for more substantive support in making meaning of the data.

Preparation for Data-Driven Decision-Making

Datnow and Park (2014) share a model to capture educators' differing abilities to utilize student data (Figure 3). They find that there are varying levels of comfort with data use, for which they provide a model from Earl and Katz (2006). The model shows stages in growth from Novice to Expert in data use, and is adapted below in Table 1. While the model seems to portray a simple growth pattern from level to level, we must also consider the work of Schildkamp, Poortman, and Handelzalts (2015). They find that teams go through varying loops of data use, in order to reach higher levels of depth in their inquiry practice. Therefore, practitioners and researchers should ensure that the model is applied in a way such that recognizes that teams move back and forth along this continuum of data use.

Table 1
Stages in Growth from Novice to Expert in Data Use. Earl and Katz (2006)

Novice				Expert
No practical experience; dependent on rules	Limited experience; dependent on rules; expects definitive answers; some recognition of patterns	Analytical; locates and considers possible patterns; internalizes key dimensions so that it's automatic	Uses analysis and synthesis; sees the whole rather than aspects; looks for links and patterns; adjusts to adapt to the context	Understand context; considers alternatives in iterative way and integrates ideas into efficient solutions; solves problems and makes ongoing adaptations automatically

Beliefs and Attitudes, and Data-Driven Decision-Making

Coburn and Turner (2011) also point out the important role that beliefs play in data use. Beliefs impact the data noticed by individuals, the interpretation of that data, and the actions taken as a response to that data. They give the example of teachers finding standardized test data or local assessments to not be valid or useful in making decisions about student instruction, or evaluating teacher effectiveness. The perceived relevance of data could impact the ultimate behaviors that teachers engage in while making data-driven decisions.

District Level Supports for Data-Driven Decision-Making

One interesting feature of the majority of the literature on data-driven decision-making is a focus on the classroom, leaving discussion of the district role mostly missing, with the exception of the previously mentioned research on the role that district offices can play in helping sites and teachers to make meaning of data use protocols.[1] There are many ways to

[1] For an overview of the research on data-driven decision-making at the district office level, see Honig and Coburn

understand the potential district role in data-driven decision-making. Honig (2008) provides an Organizational Learning Theory approach to understanding district central offices as key actors in supporting efforts in teaching and learning, a contrast from the administrative and managerial roles they have historically held. In this framework, district office staff would enter school assistance relationships, and use these relationships to determine district office policies and practices. Spillane (2012) instead would encourage researchers to look at data-driven decision-making from the perspective of Organizational Routines, placing site leaders in the position of modifying existing routines of practice in order to transform student outcomes. He does not address the central offices possible role in modifying these routines. However, it is important to note that these organizational routines take place in the context of social interactions, which leads to Honig and Venkateswaran (2012), and their view of school-central office interactions as part of a system. Site level reform efforts utilizing student data occur in the context of the school district. Honig and Venkateswaran find evidence of influence by the district on school sites, and in turn by the school sites on the district office. By contrast, others find that districts can be effective in supporting site use of data through the following strategies (Anderson et al., 2010): providing expertise on data use in schools through central office personnel, setting expectations for data use in school improvement, providing supplementary tools for facilitating data use, and developing expertise to meaningfully incorporate data into site decision making, as well as collecting district and state assessment information and providing it in a timely fashion.

Site Leadership Behaviors and Styles, and Data-Driven Decision-Making

As school leaders grapple with data-driven decision-making, there has been easy access

(2008). In summary, district office staff use data in a political context, a context that helps district office staff to create conditions to promote sustained school improvement. Public policies provide some impact but are mediated by other factors.

to prescriptive lists of steps to take in developing data-driven practices as sites in professional periodicals. In one example, Noyce (2000) identifies a list of key questions to help teachers be data-savvy:

1) Identify questions relating to student performance

2) Identify data and gather resources

3) Examine and use data

4) Ask useful questions.

These questions are embedded as part of a larger checklist that help leaders to think through the steps needed to implement a data-driven school-culture. Another example is that of Reeves (2008) with his four steps:

1) Commit to data analysis as a continuous process, not an event

2) Start with a clearly focused question

3) Develop a school wide culture of hypothesis testing

4) Go beyond the numbers to consider causes of student success and failure

While helpful, these checklists don't do as well in helping leaders to consider the messy process that often accompanies school reforms, and are often not research based, a view corroborated by Coburn and Turner(2012)as they discuss normative writing about data, work that is promoting data use, or providing a how-to guide, without actually analyzing what happens when people use data. They state that there is a lot of optimism about the use of data, but little evidence about when it should be used.

By contrast, outside of practitioners periodicals, there are several studies that have formed an initial body of literature on site leadership practices that positively influence data-driven decision-making, though the connection of data-driven practices to achievement results is currently not well-supported (Anderson et al., 2010). Principals can be considered a key resource for teachers, though quality differed from site to site. Datnow, Park, and Lewis (2013) found that principals could shape teacher's work with data through portraying data-driven decision-making as a function of collective responsibility, and establishing norms and protocols for teacher collaboration on data. One key norm is related to the notion of talking about students in a way that isn't mocking or demeaning. In addition, Park and Datnow (2009) found that principals can also encourage data-driven decision-making through distributed leadership practices, such as co-constructing a vision for implementation of data-driven decision-making. In addition, leaders emphasized an environment of continuous improvement, as opposed to one in which teachers felt blamed for the performance of their students. In an interesting contrast, Liou, Grigg, and Halverson (2014) find that a prescriptive approach to instructional leadership (as contrasted with a distributed approach) was more effective in setting up organizational structures supportive of capacity building for data-driven decision-making.

This model of continuous improvement is complementary to the findings of Marsh and Farrell (2015), which provide a core set of leadership behaviors that can serve as a blueprint for leaders. One of the key leadership practices they identify in supporting data-driven decision-making is **assessing teacher needs**, and creating goals for data use with teachers being trained. A well-defined model of growth could help leaders to set appropriate goals within the zone of proximal development for data use in the classroom. Another support by leaders that grew capacity for data-driven decision-making is **modeling** of ways to interpret, respond to, and act on data. This practice is also well supported by the work of Park and Datnow (2009). Additionally, Marsh and Farrell (2015) find that when leaders observe data-use practices, the **feedback** generated is positive and helps with the sharing of expertise with teachers. A process of **dialog**

and questioning was also identified as a key component of data-driven leadership, while **brokering** connections between teachers was useful in identifying expertise and resources to support the data process. This idea of also brokering is reinforced by Park and Datnow (2009).

Continuous Improvement and Improvement Science

These efforts to encourage data-driven decision-making through external accountability systems ultimately are about promoting school change. The most recent iteration of the California School Accountability System is emphasizing change through the process of continuous improvement. One way in which this is accomplished is through the creation of accountability results that focus on more than just a single number as the outcome (Tira, 2017). Instead, the state data considers a combination of both a number representing the status for the most recent year, as well as the change that status represents from the previous year as seen below (Figure 8). In this case, continuous improvement is encouraged through allowing schools to receive higher performance levels through either high performance, or medium performance accompanied by strong growth. By emphasizing continuous improvement, and not just an unrealistic concept of 100% proficiency for all students, the state is encouraging a system in which small but regular gains can be recognized as positive with a color of green in the same way that high, but flat achievement would be recognized with a color of green. Considering the widely varying demographics in CA Districts and Schools, and their known effect on student outcomes, this levels the playing field as stakeholders seek to navigate the accountability system.

Level	Declined Significantly (Change)	Declined (Change)	Maintained (Change)	Increased (Change)	Increased Significantly (Change)
Very High (Status)	Yellow	Green	Blue	Blue	Blue
High (Status)	Orange	Yellow	Green	Green	Blue
Medium (Status)	Orange	Orange	Yellow	Green	Green
Low (Status)	Red	Orange	Orange	Yellow	Yellow
Very Low (Status)	Red	Red	Red	Orange	Yellow

Figure 9. Sample 5x5 Grid from the California Accountability System *(Tira, 2017)*

One important framework for practitioners seeking to implement continuous improvement practices that has recently emerged in education has been the adaptation of improvement science for the K12 education setting. The roots of improvement science lie in other fields, such as health care (Rohanna, 2017), but there is demand for research-based or evidence-based solutions to problems in education. Improvement science is ideally positioned to meet those demands, with its intellectual roots deriving from Deming's system of profound knowledge as interpreted by Lemire et al. (2017). The four types of profound knowledge are:

- Knowledge of systems
- Knowledge of psychology
- Knowledge of variation
- Knowledge of how knowledge grows

Improvement science builds upon this knowledge by providing tools to apply this knowledge in order to implement rapid cycles of development of solutions, testing those solutions, and refining or discarding those solutions (known as Plan-Do-Study-Act) cycles. Once sufficiently refined, these solutions are then spread and replicated. This process is resource-intensive, requiring a significant amount of time and planning to implement (Rohanna, 2017), possibly explaining the slow spread of these ideas to K-12 education.

One handbook for improvement science implementation in educational settings by Bryk et al. (2015) shows the key role that data can play in promoting change. One chapter is centered on "Focusing on Variation in Performance". This variation must be measured, and the availability of the right data is essential towards understanding variation. Once the variation is adequately measured, good data must be collected on the effectiveness of the solutions proposed and tested through Plan-Do-Study-Act cycles. It is considered unwise to scale those solutions without the data to demonstrate their effectiveness. Ultimately, improvement science provides a framework in which data-driven decision-making can occur.

Conclusion

Persistent achievement gaps have been well known since the late 1950s, with the Brown v. Board of Education Supreme Court decision as one of the first responses to inequality of opportunities for students. These gaps have many identified causes both inside and outside of the school. Policymakers first approached these gaps as a problem that could be solved through the infusion of additional funds for students through policies such as the Elementary and Secondary Education Act, but when gaps persisted, a new policy environment encouraged the adoption of No Child Left Behind. In contrast to the ESEA, No Child Left Behind focused on student outcomes, with strong accountability provisions attached to not meeting expected benchmarks for all students. These accountability provisions encouraged schools and districts to adopt a student data focused method of decision-making called data-driven decision making.

With the strong incentives for schools to meet achievement targets for all students, data-driven decision-making has spread as a tool to help schools achieve these targets. Research has shed light on some of the most important factors that can contribute towards teachers successfully targeting student needs through data, as well as some ways in which principals can successfully lead their schools in the task of data-driven decision-making. The use of data should be part of a broader process of school improvement, a process that can be better implemented when using a rigorous framework such as that offered by improvement science. However, prior to applying improvement science to school settings, there is a gap in the research on the effectiveness of differing leadership styles and practices in improving teacher data-driven decision-making practices. This gap is key, and one that I will address through this study.

CHAPTER 3: RESEARCH DESIGN

Research Questions

In order to address the gap in understanding regarding the process of data-driven decision making as it relates to school and district leadership, the following research questions guided my study:

1) Among various kinds of data available to teachers and principals in making data-driven decisions:
    a. What is the **relative level of availability of that data**?
    b. What is the **relative frequency of use of that data?**
2) When considering conditions that potentially influence use of evidence at schools, including district office supports, principal leadership behaviors, principal leadership styles, prior training, and attitudes towards data use:
    a. To what extent **do teachers experience these conditions**?
    b. To what extent **do principals experience these conditions**?

3) To what extent do teachers engage in processes for interpreting evidence at schools?

4) Is there a relationship between types of evidence used by teachers and conditions influencing use of evidence, and the extent to which teachers engage in processes for interpreting evidence at schools?

Overview of the Research Design

To better understand this process of data driven decision-making between the district office and school sites regarding student achievement results, I developed a study of the hierarchical relationships driving data-driven decision-making by teachers embedded within schools and a principal leadership context. While the research questions posed by this study were very capable of being studied within a qualitative context, the unique contribution that this study provided was widespread testing of the findings of several other studies on data-driven leadership that pinpointed certain productive leadership behaviors such as assessing teacher needs, modeling data use, observing data practice, engaging in dialogue around data use, and brokering connections (Marsh & Farrell, 2015). Also, studies had conflicting findings regarding distributed models of leadership (Park & Datnow, 2009) versus more prescriptive models of leadership (Liou et al., 2014) in influencing teacher data-driven decision-making behaviors, a topic addressed within this study. These research questions ask about the effect of these behaviors in the hierarchical context of schools. Accordingly, Creswell's (2013) framework for research design would suggest that these research questions align with a post-positivist view of schools and the influences on behavior therein. The focus on numerical representation of behaviors, along with the desire to determine the relationship between many of the measured variables, are highly characteristic of quantitative research. Additionally, in seeking to understand the problem in relation to multiple schools the scope of the sample also supports a quantitative approach.

Research Site

The study took place in the Southern region of the State of California. The State of California represents a diverse educational environment, in which districts range in size from 650,000 students in 1,147 schools, to districts with only one school and five students. These districts also have huge variations in poverty level, ethnic make-up, and population density, providing a diverse population from which to select a district for this study. One primary district was selected for the study, with all 10 of elementary schools from that one district participating. This district in the 2016-2017 school year reported an enrollment of 10101 students, a 40.1%

free-reduced lunch percentage, a 9.1% population of English Learners, and an ethnic diversity index of 49 as reported via the ed-data.org data portal for the state of California. This district is more affluent than the state average of 58.1% free-reduced lunch and 21.4% population of English Learners. While above the average in terms of affluence, there is still a diversity of school populations in terms of demographics with Free-Reduced Lunch percentage ranging from 32.7% to 80.3%, and an English Learner percentage of 5.9% to 35.3%. One other district was recruited, and one site elected to participate from that district. The goal was to have 10 teachers participate from each site, to establish a pool of over 100 teachers for the sample.

Data Collection Methods

The primary source of data from sites was surveys of principals and teachers from 11 schools in two California school districts (Available in Appendix A and B). After obtaining the necessary clearances from the UCLA IRB and the participating districts, I administered an electronic survey that was sent to site administrators and teachers, with an initial two-week window for completion of the survey. There were at least two follow up attempts to try to raise completion rates of the survey to get to ten responses per site, occurring over several weeks past the initial two-week window for the survey. This survey was the primary tool by which to answer all four research questions. There were two main surveys: one for principals, and one for teachers. This survey was emailed directly to teachers and principals, and the survey was available for completion in the online survey platform SurveyGizmo. Participants were offered a nominal incentive for participation (a $5 Amazon gift card).

Both the principal and teacher surveys focused on questions in three categories, corresponding with elements of the theoretical framework: First, the survey asked about types of data used, as well as the relative availability of the data. Next, the survey asked about conditions influencing the use of evidence, such as the general type of leadership employed by the principal at the schools on a spectrum from distributed to more prescriptive forms of leadership. In addition, questions were asked in order to determine the level of teacher support for data-driven decision-making as represented by key leadership behaviors: assessing teacher needs, modeling data use, observing data practice, engaging in dialogue around data use, and brokering connections. Principals were also asked about their perception of district office supports for data-driven decision-making. Questions included information on prior training, as well as principal attitudes towards data-driven decision-making. Finally, the survey included questions related to perceptions of the extent to which the teacher staff engage in processes for interpreting evidence.

Data Analysis Methods

The data was analyzed using R, an open source and free statistics package available online (R Core Team, 2017). R is a robust statistics package, having first been released in 1993. While basic statistics functionality is built in to the software, it is also extendable through the download of packages to add specific analytical tools to the package. Several key packages were used in analyzing this data, including *psych* (Revelle, 2017), which facilitated basic polychoric analysis of Likert scale data, *lavaan* (Rosseel, 2012) which facilitated the confirmatory factor analysis and structural equation modeling, and *rstanarm* (Stan Development Team, 2017), an auxiliary package to RSstan (Stan Development Team, 2018), designed for the analysis of data within the Bayesian analysis framework, and Markov Chain Monte Carlo. An initial analysis focused on both the descriptive analysis of all of the varying elements of the model as delineated in the theoretical framework and the parallels and differences between principal responses and teacher responses. Then I performed confirmatory factor analyses of each group of survey questions, which then informed structural equation modeling of the overall relationship between conditions influencing teacher data-driven decision-making behaviors. A final Bayesian mixed model then helped to disentangle the hierarchical relationships embedded in the survey.

Access

Access represented a challenge for this study, due to the time needed from teachers to complete the survey. Because of the time of year where the study began (May 2017), many districts expressed hesitance about committing 15-20 minutes per teacher towards the survey. Thirteen districts were originally approached to participate in the research, with two districts ultimately providing permission to perform the survey. Principals agreed to have their teachers participate at all ten elementary schools in one district. However, the other district only had one school out of eleven possible elementary schools ultimately participate.

Management of Role

At the time of the study, I served as the Coordinator of Assessment and Accountability for the district with all ten schools participating in the survey. I did not have a direct supervisory relationship with any of the principals or teachers recruited for potential participation in the survey, limiting the potential for coercion of teachers into participation. Survey respondents' privacy was protected through stripping the results of identifiable information from the data set once the results were downloaded for analysis.

Limitations of the Design

A possible limitation of the study design was the lack of a control group. However, the study was observational in nature, and it would be difficult to design a study in which the varying conditions influencing data-driven decision-making were experimentally controlled. In addition, while the theoretical framework hypothesizes some relationships that are causal in nature, the study design does not provide a basis for proving or disproving those relationships

The research questions were constructed to primarily seek descriptive data on the variables in the study, with some attention paid to the relationship between the major categories of the framework: types of evidence, conditions influencing the use of evidence, as well as processes for use of evidence. While the survey sought to capture in a comprehensive manner the conditions influencing data use behaviors by teachers, it is possible there are other areas of school and district culture that influence the use of data in decision-making not reflected in the areas considered in the theoretical framework. In addition, the use of self-reported survey data is potentially a less accurate method of determining teacher data-driven decision-making behaviors than actually observing the behaviors, due to the possibility of teachers over-estimating data-driven behaviors that are perceived to be expected of all teachers. Finally, as the survey was self-selecting, there is the possibility that those teachers who did volunteer to participate are not representative of all teachers, with rates of participation between sites varying from 17.9% to 52.6%.

Ethical Issues

All survey instruments were submitted to the UCLA institutional review board (IRB). The study was deemed to represent a “minimal risk” to participants and was certified as exempt from review. Appropriate informed consent was obtained from all subjects at the beginning of the online administration of the survey. As stated earlier, to decrease the risk from personally identifiable data, I have anonymized the data for analysis and reporting purposes, both at the individual and site level. The participating districts, schools, and staff are not named in this report.

CHAPTER 4: RESULTS

Two school districts were recruited into the survey in the Spring of 2017. District A is a K-8 district serving approximately 10,200 students in a suburban setting in Southern California. Approximately 47.9% of students receive Free/Reduced Lunch (FRL), with 11.2% of students designated as English Learners (EL). There are 10 elementary schools in the district, and all 10 elementary schools participated in the study. District B is a K-12 district of 23,385 students also located in a suburban setting in Southern California, with 30% of students receiving Free/Reduced Lunch, with 6.5% of students designated as EL. Only one elementary school of eleven volunteered from District B. The teacher survey was administered from May to September 2017. The survey includes 104 responses from teachers from the 11 schools in the sample, out of a possible 336 teachers, an overall participation rate of 31% as shown in Table 2. In addition, principals from 9 of the 11 schools in the sample responded to the parallel principal survey, representing an 82% participation rate as noted in Table 2 below. The schools represented an average enrollment of 679 students, with a sd = 161. The average FRL percentage was 48.2% with a sd = 12.8%, and average EL percentage was 11.8% with a sd = 8.0%.

Table 2
Number of Respondents and Demographics by School (n = 104)

District	School	n	Teachers
A	A*	10	32
A	B*	10	19
A	C*	8	28
A	D	7	33
A	E*	12	30
A	F*	15	39
A	G	11	39
A	H*	8	26
A	I*	9	28
A	J*	9	34
B	K*	5	28

Note: Schools with a principal response are noted with a *

In this chapter, the survey responses will first be analyzed for descriptive results on major dimensions of data-driven decision-making as identified in the literature review. Next, the survey responses will be analyzed against principal self-reports on the parallel items in their survey to look for similarities and differences between survey groups. I will then examine the groups of survey questions to see if there is an underlying latent variable structure to those groups. Then, I will check for correlations between survey questions transformed into composite scores. Identified latent variables will be combined into a structural equation model in order to derive factor scores and create a reduced number of variables, which will be then used to create a final hierarchical model to answer the final research question.

Teacher Demographics

Teachers in the study had differing roles, with the vast majority (93) being classroom teachers. Teachers were relatively equally distributed throughout the grades, with Transitional Kinder having a smaller representation in proportion to the lesser number of TK teachers that exist in California schools in general as seen in Table 3. In addition, the majority of teachers (73) in this sample have degrees in liberal studies, with some others holding social science or arts and humanities degrees.

Table 3
Teacher Demographics (n=102)

	n	%
Grade		
TK	8	7.8
K	22	21.6
1	22	21.6
2	14	13.7
3	32	31.4
4	26	25.5
5	21	20.6
College Majors		
Arts and Humanities	9	8.8
Biological Sciences	1	1.0
Business	6	5.9
Education (Liberal Arts)	73	71.6
Other Professional (Architecture, pre-med, etc.)	1	1.0
Social Sciences	11	10.8

Note: Percentages do not add up to 100% due to some teachers reporting multiple grades taught.

In regards to teacher experience, the sample skewed heavily towards lesser amounts of experience with the current principal (Table 4/Figure 10). Almost all (n=95) of the teachers had spent four or less years with their current principal, with over forty in their first year with their principal. Experience as a teacher was more normally distributed, with a mean of 15.96 years as a teacher across the sample (Table 4, Figure 11).

Table 4
Educator Experience

	M	SD	min	max
Years with Principal	2.88	3.72	1.00	34.00
Years as a Teacher	15.96	9.15	1.00	35.00

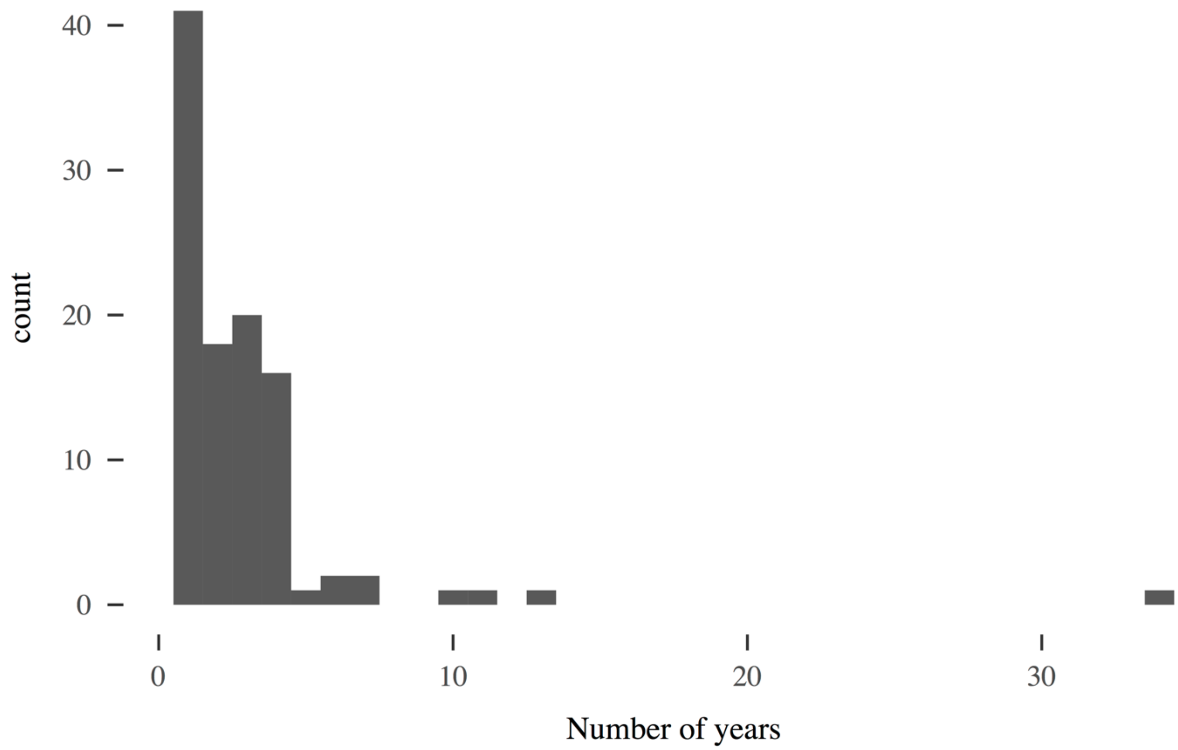

Figure 10. Histogram of Number of Years of Experience with a Principal

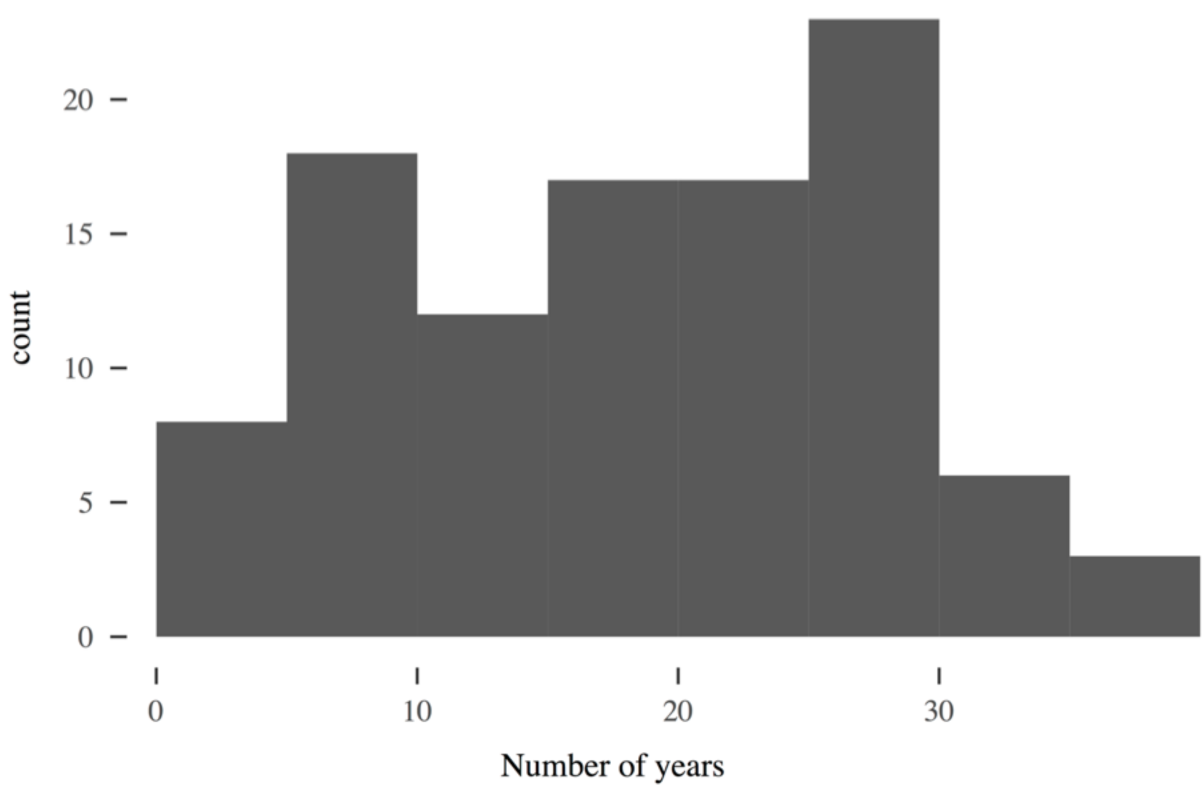

Figure 11. Histogram of Number of Years of Experience as a Teacher

Principal Demographics

Some basic demographic data was collected from responding principals (n = 9), as seen in Table 5. Principals reported an average of 2.22 years of experience at their current site. Interestingly, of the nine principals who responded to the survey, none reported more than four years at their current school site. Principals also did report higher overall experience as a principal (M = 7.78), with the most experienced principal having had 25 years in that role.

Table 5

Experience as a Principal

	M	SD	min	max
Years as Principal at Current Site	2.22	1.56	1.00	4.00
Years as a Principal Overall	7.78	9.39	0.00	25.00

Teacher Survey Descriptive Statistics

For the basic descriptive analyses that follow, survey items were treated as continuous for the purpose of analyzing the central tendency (mean) and dispersion of results (sd). While Likert-scale items generally should be treated as ordered for most statistical purposes, these measures provide a rough tool by which to examine and compare different items on a given category of questions for the survey.

Frequency of Use of Data

Teachers, when asked about the frequency of use of differing types of data, reported that suspension data was used the least, with over half (n = 60) reporting that they never use suspension data as seen in Table 6. It is possible, however, that other types of behavioral data might have been reported by teachers as being used more often, as suspensions are rare at the elementary level. Also, parent and teacher survey data is used fairly rarely, perhaps being used once a year. Summative assessments, such as state achievement data, or English learner acquisition data is used less often, also around once a year. While these assessments are offered only yearly, the results imply that teachers tend to use the data once, and don't return to it throughout the year. Instead, district created and site/teacher created assessments are used more frequently, averaging between monthly and weekly use. Finally, attendance data is utilized most often on a monthly basis by teachers.

Table 6

Frequency of Use of Different Types of Data by Teachers

Data Source	1	2	3	4	5	M	SD
State achievement data (CAASPP, CAA, SBAC, etc.)	31	51	15	7	0	1.98	0.85
English language acquisition data (CELDT, ELPAC)	5	64	21	7	5	2.44	0.89
District created/curriculum embedded assessments	4	1	57	29	12	3.43	0.86
Site/teacher created benchmarks	6	1	36	51	10	3.56	0.90
Suspension data	60	27	15	1	1	1.62	0.84
Attendance data	13	19	46	20	5	2.85	1.03
Parent survey data	24	57	18	3	2	2.06	0.83
Teacher survey data	29	51	14	5	5	2.10	1.02

Notes: 1=Never, 2=About once a year, 3=Monthly, 4=Weekly, 5=Daily, M=Mean, SD=Standard Deviation

Availability of Data

Teachers also reported on the difficulty in gaining access to differing types of data (Table 7). Suspension data was reported to be some of the most difficult data to gain access to, with a mean score of 2.59. This seems likely due to a combination of the sensitivity of such data, in combination with the relative rarity of suspension at the elementary school level. Survey data was also difficult to come by for teachers, with a mean of 2.79 for parent survey data and a mean of 2.94 for teacher survey data. State assessments are next in terms of ease, with district and site assessments having the highest ease of reported access (M = 4.24 and M = 4.43, respectively). There appears to be a trend, in which data that is more difficult to get access to has a wider variation in reported difficulty.

Table 7
Difficulty in Gaining Access to Data by Teachers

Assessment Type	1	2	3	4	5	M	SD
State achievement data (CAASPP, CAA, SBAC, etc)	9	12	31	21	28	3.47	1.26
English language acquisition data (CELDT, ELPAC)	3	12	23	28	38	3.83	1.14
District created/curriculum embedded assessments	0	6	15	31	52	4.24	0.91
Site/teacher created benchmarks	3	2	7	27	65	4.43	0.92
Suspension data	24	24	36	6	12	2.59	1.25
Attendance data	3	2	10	29	60	4.36	0.94
Parent survey data	21	21	34	13	14	2.79	1.29
Teacher survey data	20	15	39	11	19	2.94	1.33

Notes: 1=Very difficult, 5=Very easy, M=Mean, SD=Standard Deviation

Finally, one other interesting trend emerges when the frequency of use and difficulty of access are taken into joint consideration (Table 8). Data that is more frequently used is also the data that is easiest to access. While this seems like an obvious connection to make between these two survey categories, what is less obvious is the direction of influence in which this relationship exists. The more intuitive conclusion is that the ease of access leads to more frequent use by teachers, but it is also possible that the data that is used more frequently by teachers have underlying systems built in response to provide additional ease in accessing such data.

Table 8
Comparison of Frequency of Use of Data and Ease of Access

	Frequency of use		Ease of access	
Assessment Type	M	SD	M	SD
State achievement data (CAASPP, CAA, SBAC, etc)	1.98	0.85	3.47	1.26
English language acquisition data (CELDT, ELPAC)	2.44	0.89	3.83	1.14
District created/curriculum embedded assessments	3.43	0.86	4.24	0.91
Site/teacher created benchmarks	3.56	0.9	4.43	0.92
Suspension data	1.62	0.84	2.59	1.25
Attendance data	2.85	1.03	4.36	0.94

Parent survey data	2.06	0.83	2.79	1.29
Teacher survey data	2.10	1.02	2.94	1.33

Expertise of Teachers in Using Data

Teachers when reporting expertise in using different forms of data (Table 9) felt most proficient using those academic measures closest to the school site, such as site/teacher created benchmarks (M = 3.32) and district created assessments (M = 3.18). The next highest expertise was reported for attendance data (M = 2.73. The remaining forms of data are all fairly low by comparison, though teacher survey data and English Learner acquisition data surprisingly surpass State achievement data in reported proficiency by teacher. To better understand these results, I disaggregated the responses concerning State Achievement data by grade (Table 10). Once displayed in this manner, there is a positive trend in expertise as the teacher grade increases, partially explaining the low average results on the expertise measure. This positive trend can be explained by the fact that State Achievement tests are not required until the 3rd grade, diminishing the use and consequently the expertise.

Table 9
Expertise in the Use of Different Forms of Data by Teachers

	1	2	3	4	M	SD
State achievement data (CAASPP, CAA, SBAC, etc)	24	26	44	9	2.37	0.94
English language acquisition data (CELDT, ELPAC)	11	28	55	10	2.62	0.80
District created/curriculum embedded assessments	2	11	57	34	3.18	0.69
Site/teacher created benchmarks	3	8	46	47	3.32	0.74
Suspension data	46	33	21	3	1.82	0.86
Attendance data	10	25	51	17	2.73	0.85
Parent survey data	28	28	39	9	2.28	0.96
Teacher survey data	20	27	41	16	2.51	0.98

Notes: 1=Basic, 2=Intermediate, 3=Proficient, 4=Advanced, M=Mean, SD=Standard Deviation

Table 10
Expertise in the Use of State Achievement Data by Grade Level Taught

Grade	1	2	3	4	M	SD
TK/K	16	1	9	4	2.03	1.19
1	6	7	6	2	2.19	0.98
2	3	4	5	2	2.43	1.02
3	2	9	16	5	2.75	0.80
4	1	7	16	2	2.73	0.67
5	1	2	13	5	3.05	0.74

Notes: 1=Basic, 2=Intermediate, 3=Proficient, 4=Advanced, M=Mean, SD=Standard Deviation

Perceptions of Relevance of Data by Teachers

Teachers were asked to consider the relevance of differing types of data along four dimensions: setting goals and actions for school wide planning (Table 11), determining teacher effectiveness/evaluation (Table 12), adjusting core curriculum and instruction for students (Table 13), and identifying students for behavioral or academic intervention (Table 14). Interestingly, many of the same trends regarding the types of data with the highest ratings by teachers are much the same as in the other survey question groups, such as frequency of use, availability of data, and expertise. Local measures such as site and district benchmarks tend to be viewed as more relevant, followed closely by English learner data and State achievement data. Attendance data, suspension data, and survey data tend to be viewed as having lower relevance.

An interesting alternate way of looking at the results was comparing the four dimensions of data use. When considered this way, the trend that is most obvious is that teachers tended not to believe that any of the data types were appropriate for use in determining teacher effectiveness. The one mild exception was that of site/teacher benchmarks, which had a slightly higher average support among teachers for that purpose. There is a certain logic in teachers finding assessments of their own creation to be the most relevant data among those listed to determine their own effectiveness. Beyond teacher effectiveness, data on average was seen as moderately relevant for setting goals and actions for school wide planning, and slightly more relevant for adjusting core curriculum and instruction, and identifying students for academic and behavioral intervention.

Table 11
Relevance of data in making decisions in the area of ***setting goals and actions for schoolwide planning***

	1	2	3	4	M	SD
State achievement data (CAASPP, CAA, SBAC, etc.)	11	18	33	41	3.01	1.00
English language acquisition data (CELDT, ELPAC)	2	20	39	40	3.16	0.81
District created/curriculum embedded assessments	6	26	29	39	3.01	0.95
Site/teacher created benchmarks	6	22	35	36	3.02	0.91
Suspension data	18	33	29	19	2.49	1.00
Attendance data	6	27	30	36	2.97	0.94
Parent survey data	14	37	35	13	2.47	0.90
Teacher survey data	9	26	40	25	2.81	0.92

Notes: 1=Not at all, 2=Somewhat, 3=Moderately, 4=Extremely, M=Mean, SD=Standard Deviation

Table 12
Relevance of data in making decisions in the area of ***determining teacher effectiveness/evaluation***

	1	2	3	4	M	SD
State achievement data (CAASPP, CAA, SBAC, etc.)	44	29	23	7	1.93	0.96
English language acquisition data (CELDT, ELPAC)	37	33	22	9	2.03	0.97
District created/curriculum embedded assessments	25	36	29	11	2.26	0.96
Site/teacher created benchmarks	17	31	30	20	2.54	1.01
Suspension data	60	24	12	4	1.60	0.85
Attendance data	60	22	10	8	1.66	0.96
Parent survey data	38	46	14	2	1.80	0.75
Teacher survey data	38	31	23	9	2.03	0.98

Notes: 1=Not at all, 2=Somewhat, 3=Moderately, 4=Extremely, M=Mean, SD=Standard Deviation

Table 13
Relevance of data in making decisions in the area of ***adjusting core curriculum and instruction for students***

	1	2	3	4	M	SD
State achievement data (CAASPP, CAA, SBAC, etc.)	15	24	29	35	2.82	1.06
English language acquisition data (CELDT, ELPAC)	3	17	39	41	3.18	0.82
District created/curriculum embedded assessments	3	16	40	41	3.19	0.81
Site/teacher created benchmarks	3	11	38	46	3.30	0.79
Suspension data	46	33	17	4	1.79	0.87
Attendance data	33	32	25	10	2.12	0.99
Parent survey data	25	46	25	3	2.06	0.79
Teacher survey data	14	21	43	23	2.74	0.97

Notes: 1=Not at all, 2=Somewhat, 3=Moderately, 4=Extremely, M=Mean, SD=Standard Deviation

Table 14
Relevance of data in making decisions in the area of ***identifying students for academic or behavioral intervention***

	1	2	3	4	M	SD
State achievement data (CAASPP, CAA, SBAC, etc.)	15	35	24	24	2.58	1.02
English language acquisition data (CELDT, ELPAC)	5	25	29	37	3.02	0.93
District created/curriculum embedded assessments	7	25	38	27	2.88	0.90
Site/teacher created benchmarks	6	16	31	44	3.16	0.92
Suspension data	19	21	23	33	2.73	1.14
Attendance data	10	28	29	27	2.78	0.99
Parent survey data	26	44	18	9	2.10	0.91
Teacher survey data	18	24	36	19	2.58	1.01

Notes: 1=Not at all, 2=Somewhat, 3=Moderately, 4=Extremely, M=Mean, SD=Standard Deviation

Training and Support for Data-Driven Decision-Making

When asking teachers regarding effective training or support in data-driven decision-making teachers reported relatively similar levels of effectiveness among the six settings identified in the survey (Table 15). Undergraduate degree programs received the lowest average rating, with an interesting bimodal distribution and spike in teachers reporting no training at all in their undergraduate programs. Team level collaboration receives the most credit for effectiveness (M = 3.22), while other district (M = 3.07) and site level (M = 3.01) staff receive positive support from teachers as also being effectives sources of training.

Table 15
Extent of effective training or support in data-driven decision-making in differing settings

	1	2	3	4	M	SD
Undergraduate degree program	32	18	40	13	2.33	1.05
Teacher preparation program (credential program)	11	21	42	29	2.86	0.95
School district sponsored staff development	3	20	47	33	3.07	0.80
Professional conferences	12	25	42	24	2.76	0.94
Site level staff development	6	19	46	32	3.01	0.86
Team level collaboration	3	16	39	45	3.22	0.82

Notes: 1=None at all, 2=Only a little, 3=Some, 4=A lot, M=Mean, SD=Standard Deviation

Principal Leadership Style and Expectations

Next, moving onto principal level measures, the first set of measures are intended to capture leadership style, specifically that of a distributed leadership style as opposed to a more prescriptive style of leadership (Table 16). This data was surprising in that teachers seemed to have a fairly strong sense of their principals as employing distributed leadership practices, as indicated by the higher means on these items. My expectation was more variation, with principals being reported to have both distributed and prescriptive leadership styles. The highest indicator of distributed leadership style was that of developing a joint vision (M = 4.38), while staff also felt empowered in instructional decision-making (M = 4.25). Teachers described the lowest level of distributed leadership style in regards to professional development plans (M = 3.80), and especially in regards to making decisions about the allocation of financial resources (M = 3.49).

Table 16
Frequency of principal leadership style behaviors

	1	2	3	4	5	M	SD
Develop and implement a joint vision with the staff regarding and purposes and aspirations of the school	0	4	13	23	58	4.38	0.87
Set and monitor sitewide goals for student outcomes with staff	4	2	12	42	39	4.11	0.98
Empower staff in instructional decision making in regards to curriculum and pedagogical strategies	1	6	12	28	52	4.25	0.96
Evaluate and implement professional development plans with site staff	5	7	21	36	30	3.80	1.11
Make decisions with site staff regarding the allocation of financial resources	7	14	24	31	23	3.49	1.20
Encourage a commitment to shared accountability for student outcomes from all staff	1	7	14	30	47	4.16	0.99

Notes: 1=Never, 5=All the time, M=Mean, SD=Standard Deviation

The survey also measured principal expectations in regards to data-driven decision-making (Table 17). The results for this question also have an interesting bimodal distribution, with almost half (n = 48) of the teachers strongly agreeing that the principal expects teachers to use data. However, a fifth of the teachers (20) strongly disagreed with the statement. In addition, seven teachers didn't know what their principal's expectations were, a somewhat surprising result considering the larger systematic reliance on data for decision-making. However, this lack of knowledge could be a result of the relatively large number of teachers in their first year with their current principal.

Table 17
Level of agreement with statement that the principal expects teachers in the school to use data to make decisions about instruction

1	2	3	4	5	M	SD
20	2	7	22	48	3.77	1.56

Notes: 1=Strongly disagree, 2=Disagree, 3 =I don't know, 4=Agree, 5=Strongly agree, M=Mean, SD=Standard Deviation

Principal Leadership Behaviors

The survey asked about the six principal leadership behaviors that were identified in the literature that promoted data-driven decision-making among teachers (Table 18). Principals on average asked questions regarding past data-driven decision-making less often (M = 3.19) than other behaviors seen more often, such as demonstrating the process of making instructional decisions in response to data (M = 3.74), or designating time during collaboration for data analysis (M = 3.84). While these responses are skewed slightly towards the left, there is enough variation to provide a solid basis for analysis. In general, principal behaviors requiring group level action tended to have higher ratings than those behaviors requiring one on one support.

Table 18
Frequency of principal data-driven leadership behaviors

	1	2	3	4	5	M	SD
Ask questions about your past experience with using student data to inform decision-making	11	14	30	33	11	3.19	1.16
Designate time during collaboration or shared planning for data analysis or decision-making	2	12	19	33	33	3.84	1.09
Lead analyses of school or classroom data with site staff	3	9	22	42	23	3.74	1.02
Demonstrate the process of making instructional decisions in response to data	6	12	24	37	20	3.54	1.13
Observe and provide direct feedback of your practices in analyzing and using data	8	16	25	38	11	3.29	1.12
Engage in dialogue with you regarding your process of data analysis or instructional decision making	10	13	29	34	13	3.27	1.16

Notes: 1=Never, 5=All the time, M=Mean, SD=Standard Deviation

District Leadership Supports and Expectations for Data Driven Decision Making

When considering teacher supports for data-driven decision-making (Table 19), teachers rated lowest the amount of expertise on data use provided through central office personnel (M = 2.94) and rated most highly the role of the district in collecting district and state assessment information and providing it in timely fashion (M = 3.40). The next highest rating went towards the providing of supplementary technological or other tools for data use (M = 3.24). This rating may actually be the more impactful of the two highest ratings, considering that district and state assessment data was consistently rated lower than site data on earlier measures.

Table 19
Frequency of district office data-driven decision-making supports

	1	2	3	4	5	M	SD
Provide expertise on data use through central office personnel	6	25	41	21	5	2.94	0.96
Set expectations for data use in school improvement	7	24	32	21	13	3.09	1.14
Provide supplementary technological or other tools for facilitating data use	6	15	38	27	12	3.24	1.06
Develop expertise through professional development to meaningfully incorporate data use into decision making	7	22	41	19	8	2.99	1.03
Collect district and state assessment information and provide it in a timely fashion for sites	6	14	29	33	16	3.40	1.11

Notes: 1=Never, 5=All the time, M=Mean, SD=Standard Deviation

As for district expectations, teachers once again responded with a bimodal distribution, through there was a less significant proportion (n = 13) reporting that they strongly disagreed with the statement regarding expectations for data use (Table 20). Also, teachers were less likely to report that they strongly agreed with the statement (n = 28). Expectations were reported lower from the district than principals (M = 3.23 versus M = 3.77), but variation was lower in district results (SD = 1.17 versus SD = 1.56).

Table 20
Level of agreement with statement that the district expects teachers in the school to use data to make decisions about instruction

1	2	3	4	5	M	SD
13	2	11	44	28	3.23	1.17

Notes: 1=Strongly disagree, 2=Disagree, 3 =I don't know, 4=Agree, 5=Strongly agree, M=Mean, SD=Standard Deviation

District Local Control Accountability Plan and Teacher Knowledge and Perceptions

One last general area of district impact on teaching is that of the Local Control Accountability Plan (LCAP). The survey asked teachers regarding their knowledge (Table 21), as well as their perception of the effect of the Local Control Accountability Plan on their practice as a teacher (Table 22). Knowledge of the LCAP was remarkably consistent among all of the different aspects of the plan, with an average ranging from between M = 2.51, and M = 2.66. In addition, in terms of effect, many more teachers than average (one out of every three) responded with Not Applicable, resulting in the inclusion of this category for this particular table. Those remaining were also pretty ambivalent, with the majority of remaining teachers reporting the LCAP to have had neither a negative or positive impact, with a slight skew towards positive impacts, with one key exception. Interestingly, teachers had a lower opinion of the effects of LCAP on school site budgets.

Table 21

How much knowledge do you have regarding the following elements of the Local Control Accountability Plan?

	1	2	3	4	M	SD
LCAP Goals for the School District	22	33	36	7	2.66	0.64
LCAP Actions and Services for All Students	23	35	36	3	2.57	0.58
LCAP Actions and Services for Low Income Students	23	37	33	4	2.55	0.6
LCAP Actions and Services for English Learners	22	31	37	7	2.68	0.64
LCAP Actions and Services for Foster Youth	25	38	29	5	2.54	0.63
LCAP Metrics/Annual Measurable Outcomes	27	37	29	3	2.51	0.58

Note: 1=None at all, 2=Only a little, 3=Some, 4=A lot; M=Mean, SD=SD

Table 22
How much effect has the Local Control Accountability Plan had on your practice as a teacher in the following areas last year?

	1	2	3	4	5	6	7	NA	M	SD
Data-driven decision-making practices	2	2	2	31	16	8	2	35	4.41	1.16
Student curriculum	2	3	9	28	14	4	4	34	4.20	1.27
Intervention programs for at-risk students	2	3	5	25	15	11	5	32	4.53	1.36
Classroom Instructional strategies	1	NA	2	31	10	14	4	36	4.73	1.15
School discipline/behavior systems	4	5	5	22	13	8	4	37	4.23	1.52
School Site Budgets	2	8	13	29	6	3	3	34	3.78	1.29
Personnel Decisions	4	2	7	30	6	5	3	41	4.04	1.36

Note: 1=Completely negative, 2=Very negative, 3=Somewhat negative, 4=Neither negative or positive, 5=Somewhat positive, 6=Very positive, 7=Completely Positive, NA = Not applicable, M=Mean, SD=Standard Deviation

Teacher Behaviors in Using Student Data

Teacher results in regards to behaviors in using student data were self-reported by teachers to be extremely high, resulting in the highest means among all survey items (Table 23). Only one item was reported to be below an average of four: jointly analyzing data with other teachers to meet student needs. The other six behaviors were reported to be above 4, ranging from M = 4.31 for setting class goals and targets, through M = 4.72 in identifying students to target for intervention. On all of these six measures, a majority of teachers reported that they engaged in these behaviors all of the time, results in the strong skew towards the left.

Table 23
Teacher Behaviors in Using Student Data

	1	2	3	4	5	M	SD
Set individual student improvement goals and targets	0	1	12	26	60	4.46	0.75
Set class improvement goals and targets	1	4	11	30	53	4.31	0.90
Analyze aggregate data with other	3	6	19	44	28	3.88	0.99

teachers to inform joint action in meeting student needs							
Tailor instruction for the whole class	0	3	10	28	59	4.43	0.79
Divide students into small groups to provide interventions	0	1	5	23	71	4.64	0.63
Change instructional strategies for individual students	0	0	4	36	60	4.56	0.57
Identify students to target for intervention	0	1	4	17	77	4.72	0.59

Notes: 1=Never, 5=All the time, M=Mean, SD=Standard Deviation

Principal Survey Comparisons to Teacher Survey

Another interesting dimension is comparing the principal's perceptions on parallel measures to that of the teacher measure. This comparison serves a key purpose: it is a way to judge whether principals have a strong sense of teacher perceptions on issues relating to data-driven decision-making. To do so, I calculated a custom metric, utilizing a custom formula derived from the calculation for standard deviation. The first step was to compute the difference in integer representations of the Likert responses between principals and teachers. These differences were then summed, divided by the number of responses, and the square root was taken of that sum in order to generate a difference score. The formula is as seen below:

$$d_{jk} = \sqrt{\frac{1}{n_j}\sum_{i=1}^{n_j}\left(t_{ijk} - p_{jk}\right)^2}$$

Where:

d_{jk} = *difference score*
t_{ijk} = rating of teacher i at school j on item k
p_{jk} = rating of the school j principal on item k
n_j = number of teachers responding from school j

School-wide averages per item also derived using the following formula, where K is the number of items:

$$d_j = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\frac{1}{n_j}\sum_{i=1}^{n_j}\left(t_{ijk} - p_{jk}\right)^2}$$

Item averages were computed using the following formula, where J is the number of schools:

$$d_k = \sqrt{\frac{1}{J}\sum_{j=1}^{J}\frac{1}{n_k}\sum_{i=1}^{n_k}\left(t_{ijk} - p_{jk}\right)^2}$$

An initial analysis of overall differences across all questions and responses for a site reveals that there is some variation in difference scores (Table 24), with principal K having the highest difference score across all questions (d = 1.46), and principal H having the lowest difference score (d = 1.22). I will analyze variation between teacher responses and principal responses on individual question groups using the difference score as computed above, as well through the use of a modified box plot in the upcoming sections. In the case of the modified box plot, the whiskers represent the range of teacher responses, and the box edges represent one standard deviation from the mean, as represented by the center line of the box plot. Principal responses are charted on these box plots using a single dot.

Table 24
Average Difference Score Across 102 Questions

School	Difference Score
A	1.26
B	1.34
C	1.24
E	1.41
F	1.33
H	1.22
I	1.29
J	1.33
K	1.46

Note: Principals from schools D and G did not respond and are not included in these calculations

Frequency of Use of Data

When considering the frequency of use of varying types of data (Table 25/Figure 12), suspension data has one of the highest difference scores (d = 1.31) between principal and teacher survey results, with four of the nine principals overestimating the use of such data. Only attendance data reflected a higher difference score (d = 1.56), but for attendance data, principals both over and underestimated their teachers self-reported use of such data. One possible explanation is that for teachers, suspensions occur so rarely at the elementary level that the data would not have the same relevance for teachers as for administrators.

Table 25
Average Difference Score Across Questions Regarding Frequency of Data Use

question	A	B	C	E	F	H	I	J	K	ALL
t11often_att	1.61	2.00	1.25	2.63	1.00	0.79	1.20	0.88	1.18	1.56
t11often_bench	1.14	0.71	1.27	0.76	1.03	0.87	0.94	1.41	0.63	1.01
t11often_dist	1.00	1.18	0.94	1.21	1.18	0.61	0.47	1.00	0.63	0.99
t11often_el	0.95	1.05	1.12	1.04	0.86	1.12	1.20	0.94	1.84	1.09
t11often_parent	0.63	1.14	0.79	1.58	0.73	0.61	1.25	0.94	0.45	1.00
t11often_state	1.22	0.63	1.41	0.65	1.24	1.06	1.37	1.00	1.95	1.17
t11often_susp	0.71	0.45	1.73	1.83	1.61	0.79	0.94	1.49	0.89	1.31
t11often_teacher	0.77	1.95	1.06	1.26	1.03	1.27	1.70	0.82	0.63	1.25
ALL	1.05	1.26	1.23	1.50	1.11	0.92	1.18	1.09	1.16	

Note: att = Attendance, bench = Teacher/site created assessments, dist = District assessments, el = English Learner language data, parent = Parent survey results, state = State assessment results, susp = Suspension data, teacher = Teacher survey results

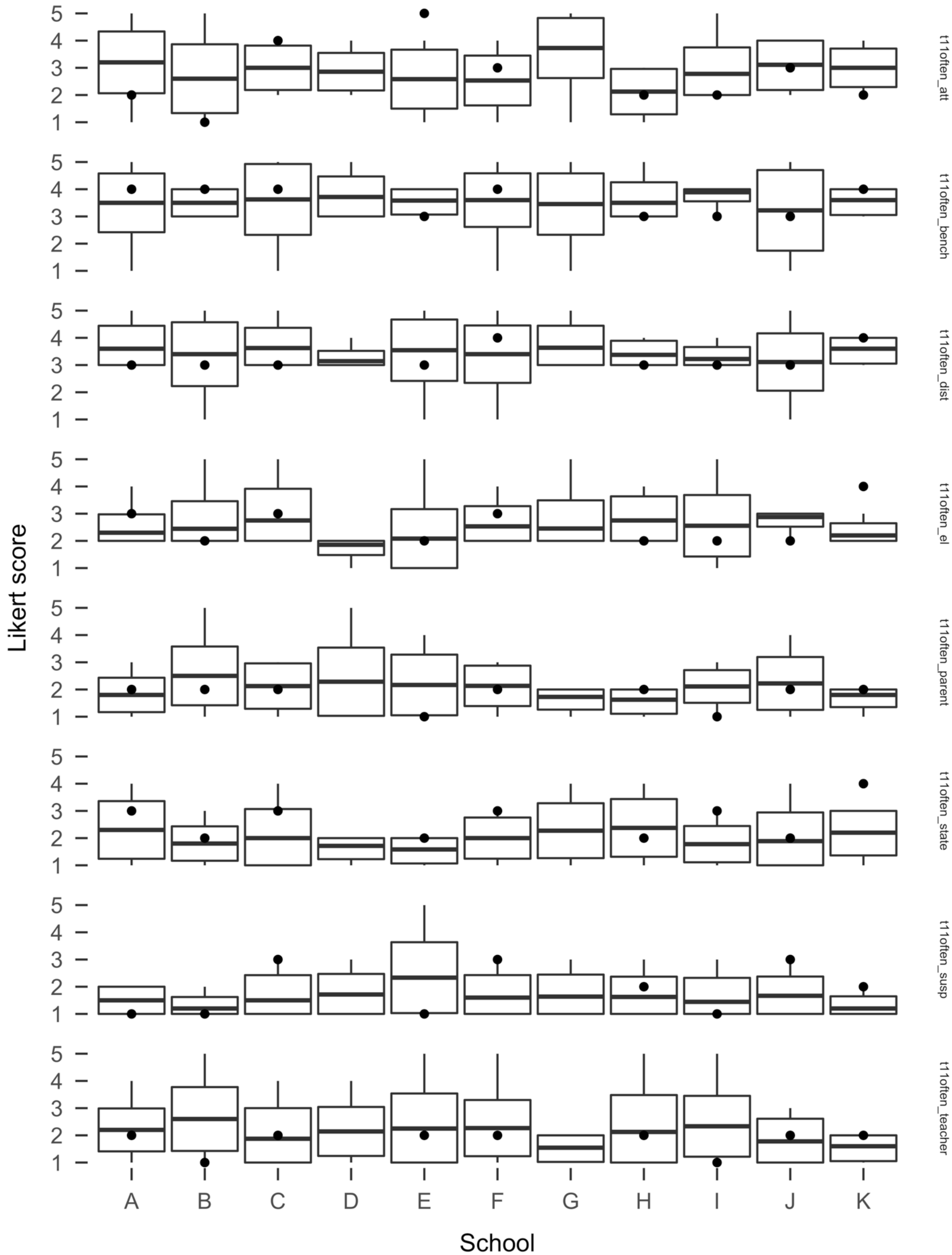

Figure 12. Plot of Teacher and Principal Responses Regarding Frequency of Data Use

Availability of Data

As compared with frequency of use of data, overall difference scores are higher for self-reported difficulty in access to data (Table 26/Figure 13), with five of the eight data types with a difference score higher than 1.75 (EL Data, Parent survey data, state assessment results, suspension data, and teacher survey data). Generally, principals on those items responded that data was easier to access than their sites' teachers, with the exception of site E, where the principal reported all of the five data types as representing the highest difficulty of access. All other principals on these data types tended to underestimate the difficulty of access by comparison.

Table 26
Average Difference Score Across Questions Regarding Difficulty of Access to Data

question	A	B	C	E	F	H	I	J	K	ALL
t12diff_att	1.61	2.68	1.00	0.91	1.13	1.37	0.75	1.33	2.53	1.54
t12diff_bench	1.55	0.00	1.32	0.96	1.46	0.61	0.94	1.20	1.10	1.14
t12diff_dist	0.71	0.00	0.79	1.04	1.18	1.41	0.82	1.15	1.84	1.05
t12diff_el	1.26	1.70	0.79	2.65	1.86	1.41	2.47	1.56	0.89	1.81
t12diff_parent	1.00	1.90	1.66	2.61	1.81	1.46	1.37	1.80	2.19	1.81
t12diff_state	1.22	1.45	1.32	2.16	1.75	2.12	2.56	2.29	1.55	1.89
t12diff_susp	1.10	1.87	2.30	2.06	1.69	1.54	1.76	1.73	1.79	1.78
t12diff_teach	1.00	2.02	1.66	2.69	1.69	1.41	1.15	1.73	2.19	1.81
ALL	1.21	1.71	1.42	2.02	1.59	1.47	1.62	1.63	1.84	

Note: att = Attendance, bench = Teacher/site created assessments, dist = District assessments, el = English Learner language data, parent = Parent survey results, state = State assessment results, susp = Suspension data, teacher = Teacher survey results

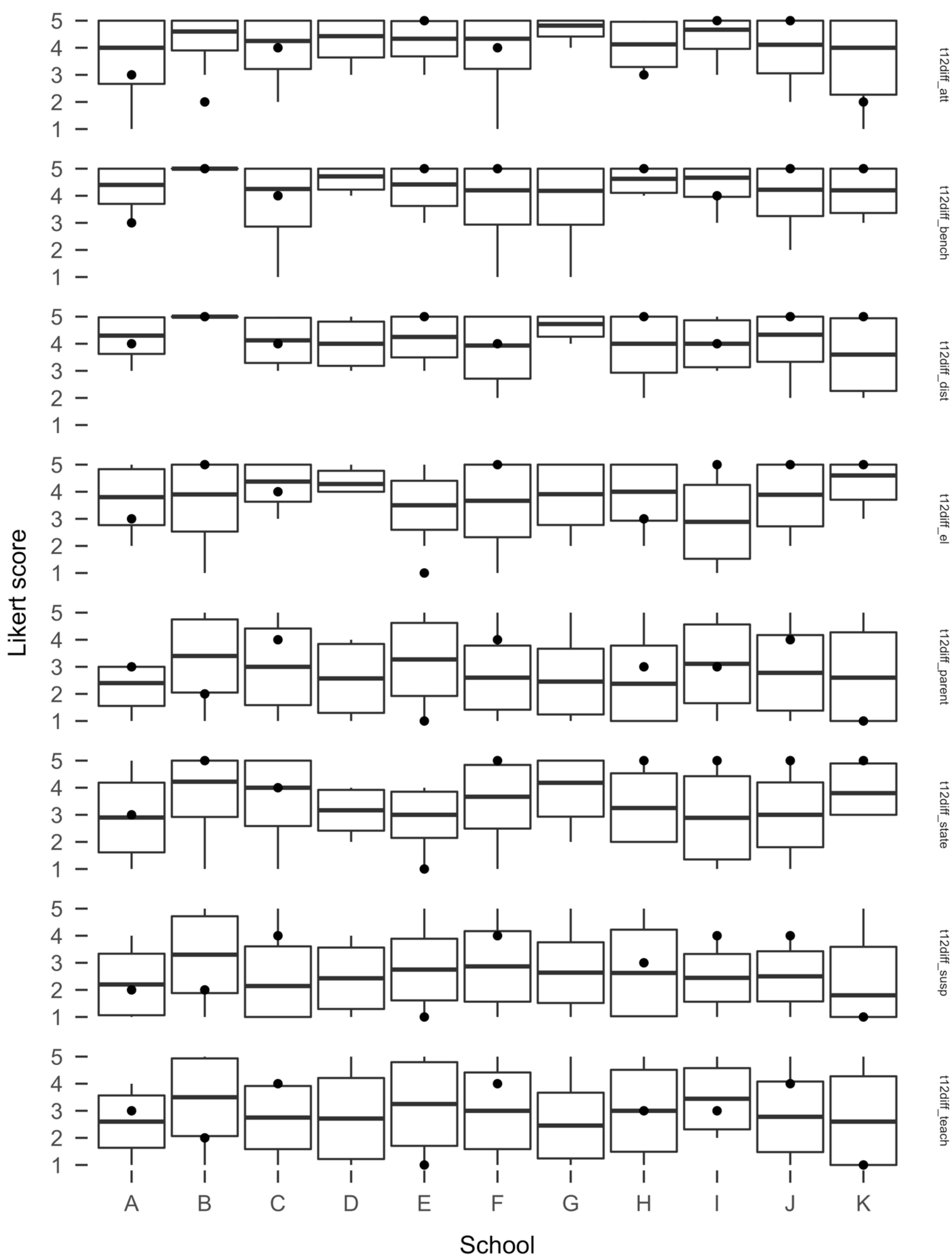

Figure 13. Plot of Teacher and Principal Responses Regarding Accessibility of Data

Expertise of Teachers in Using Data

Principals and teachers are fairly well aligned when it comes to the expertise of teachers in using differing data types, with the highest difference score of a 1.53 in regards to attendance data (Table 27/Figure 14). Difference scores were lowest for EL data at a 1.10, through State assessment data was close behind with a 1.15. When looking at responses by site and item, an interesting trend appears. For the vast majority of responses, when principals' predictions were outside of one-standard deviation from the average teacher response, they tended to underestimate teachers' expertise. Overall, principals are fairly accurate in assessing teacher's expertise in using data, but when they do make assign a rating that does not match their surveyed teachers, they tend to underestimate the responses from their teachers. One possibility is that the principal is considering all teachers, who may differ in some substantive way from the portion of the teaching staff that agreed to participate in the study.

Table 27
Average Difference Score Across Questions Regarding Expertise in Using Data

question	A	B	C	E	F	H	I	J	K	ALL
t13expert_att	1.70	1.90	0.61	2.02	1.39	1.17	1.25	0.82	2.24	1.53
t13expert_bench	1.45	0.77	1.06	2.52	1.06	0.71	0.75	0.67	1.48	1.33
t13expert_dist	1.38	0.71	0.79	2.25	1.29	0.61	0.67	0.58	0.89	1.22
t13expert_el	1.34	1.00	0.35	1.78	0.77	1.41	0.58	0.94	1.79	1.18
t13expert_parent	1.52	1.76	1.12	1.41	1.06	1.12	1.00	1.15	1.41	1.30
t13expert_state	1.14	0.89	1.12	1.47	1.03	0.87	1.00	1.37	1.26	1.15
t13expert_susp	0.71	1.52	1.56	1.04	1.39	0.87	0.58	1.67	1.34	1.24
t13expert_teacher	1.67	2.26	1.00	1.76	0.97	1.12	1.20	1.20	1.41	1.46
ALL	1.40	1.46	1.00	1.84	1.14	1.02	0.91	1.11	1.52	

Note: att = Attendance, bench = Teacher/site created assessments, dist = District assessments, el = English Learner language data, parent = Parent survey results, state = State assessment results, susp = Suspension data, teacher = Teacher survey results

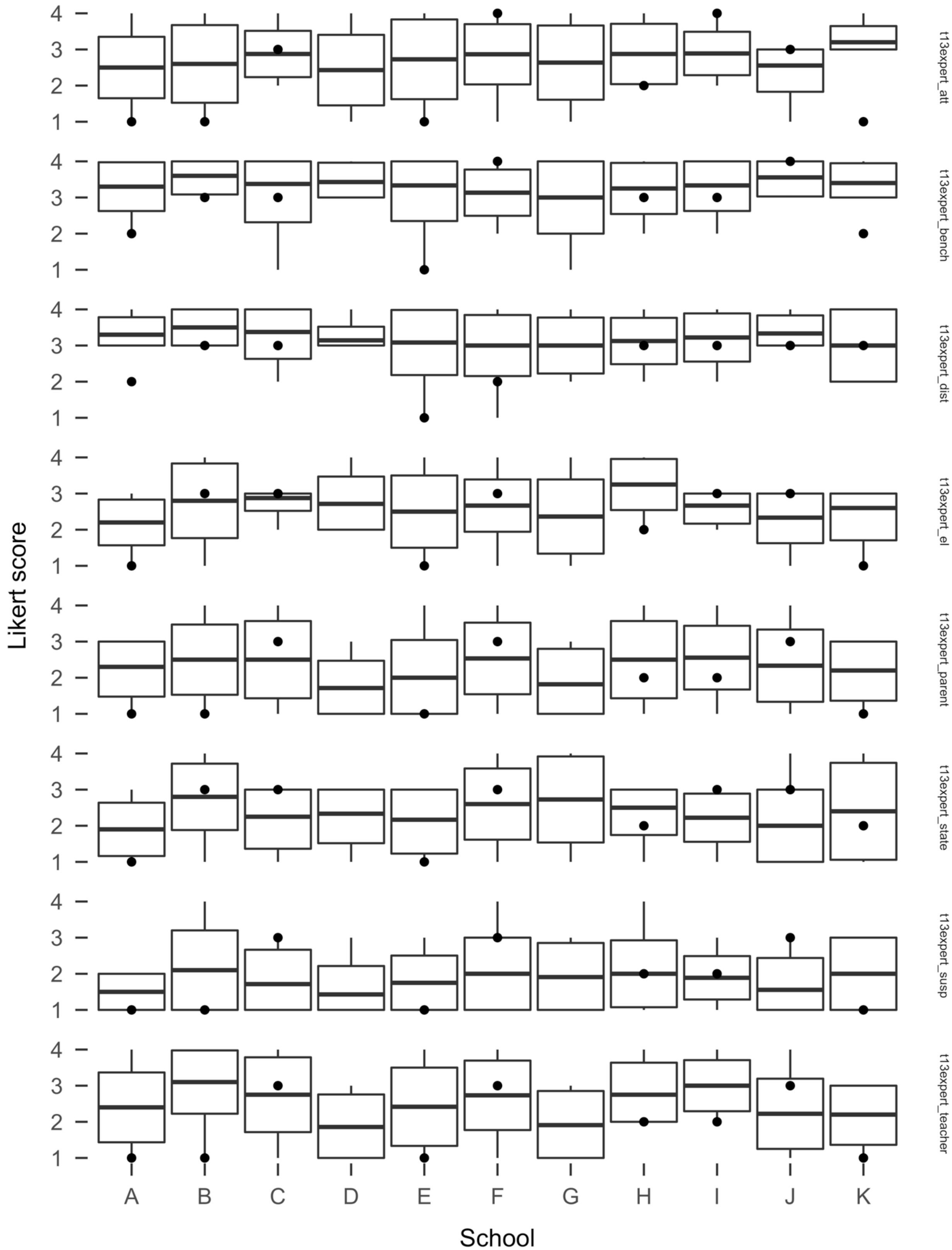

Figure 14. Plot of Teacher and Principal Responses Regarding Expertise in Using Data

Perceptions of Relevance of Data by Teachers

These set of questions centered on the perceptions of the relevance to teachers of differing data sources to four key dimensions: relevance to curriculum and instruction (Table 28/Figure 15), relevance to setting sitewide goals and actions (Table 29/Figure 16), relevance to intervention (Table 30/Figure 17), and relevance to teacher evaluation (Table 31/Figure 18). When comparing between these groups, principals and teachers tended to be best aligned when considering the role of data towards teacher evaluation (in that they tended to not see it as relevant.) By contrast, the relevance of data to intervention had the highest variation, caused by principals tending to ascribe more importance to data than teachers. Relevance to curriculum and instruction, and to school goals feel in the middle in terms of difference scores, and no obvious trends appear when analyzing teacher versus principal responses.

Table 28
Average Difference Score Across Questions Regarding Relevance of Data to Curriculum and Instruction

question	A	B	C	E	F	H	I	J	K	ALL
t15rel2ci_att	0.95	1.52	1.58	1.12	1.24	1.07	0.88	1.41	1.79	1.28
t15rel2ci_bench	2.16	1.05	1.13	0.76	0.92	1.00	1.58	0.71	0.63	1.19
t15rel2ci_dist	1.00	0.95	1.00	1.41	1.30	1.06	0.75	0.94	1.32	1.11
t15rel2ci_el	1.38	0.75	0.61	1.41	1.21	0.87	0.75	0.79	0.63	1.04
t15rel2ci_parent	0.71	1.00	0.79	1.12	0.96	0.65	0.94	0.94	1.41	0.96
t15rel2ci_state	1.30	0.71	0.71	1.26	1.44	1.17	1.80	1.00	1.41	1.26
t15rel2ci_susp	1.29	1.22	1.54	0.76	0.96	1.00	0.88	0.79	1.34	1.09
t15rel2ci_teacher	1.00	0.84	1.37	1.00	0.68	0.71	1.29	1.32	2.10	1.12

Note: att = Attendance, bench = Teacher/site created assessments, dist = District assessments, el = English Learner language data, parent = Parent survey results, state = State assessment results, susp = Suspension data, teacher = Teacher survey results

Table 29
Average Difference Score Across Questions Regarding Relevance of Data to Schoolwide Goals

question	A	B	C	E	F	H	I	J	K	ALL
t15rel2goals_att	0.95	1.14	1.36	2.24	0.88	0.65	1.29	1.00	1.67	1.34
t15rel2goals_bench	2.02	0.84	1.60	1.00	1.00	1.12	1.58	1.06	1.48	1.32
t15rel2goals_dist	0.77	1.14	1.17	1.29	1.08	1.06	1.00	0.87	1.41	1.09
t15rel2goals_el	0.84	1.05	0.79	1.55	1.27	0.79	1.00	1.17	0.77	1.10
t15rel2goals_parent	1.10	1.00	2.00	1.80	0.96	1.22	1.00	1.17	0.77	1.29
t15rel2goals_state	1.67	1.05	0.61	1.44	1.03	1.46	1.91	1.32	1.48	1.36
t15rel2goals_susp	0.82	1.26	1.36	2.18	1.07	0.61	1.20	1.06	0.89	1.30
t15rel2goals_teacher	0.89	0.84	1.69	1.38	0.73	0.79	1.11	1.12	1.34	1.10

Note: att = Attendance, bench = Teacher/site created assessments, dist = District assessments, el = English Learner language data, parent = Parent survey results, state = State assessment results, susp = Suspension data, teacher = Teacher survey results

Table 30
Average Difference Score Across Questions Regarding Relevance of Data to Intervention

question	A	B	C	E	F	H	I	J	K	ALL
t15rel2int_att	1.15	1.41	1.06	1.89	1.00	1.13	1.76	1.06	1.10	1.36
t15rel2int_bench	1.33	0.82	1.27	1.00	1.00	2.00	2.37	0.71	1.67	1.40
t15rel2int_dist	1.29	1.05	1.46	1.22	1.51	2.26	0.75	0.71	1.48	1.36
t15rel2int_el	1.25	0.94	0.94	1.53	1.14	2.09	1.00	1.06	1.73	1.33
t15rel2int_parent	0.82	1.15	2.24	1.08	1.09	0.61	1.15	1.22	1.18	1.23
t15rel2int_state	1.33	1.00	0.71	1.19	1.14	1.62	1.29	1.06	1.90	1.25
t15rel2int_susp	1.22	1.83	1.54	1.71	1.60	1.12	1.89	1.27	1.90	1.59
t15rel2int_teacher	0.82	0.67	1.84	0.96	0.85	1.06	1.11	1.94	1.61	1.23

Note: att = Attendance, bench = Teacher/site created assessments, dist = District assessments, el = English Learner language data, parent = Parent survey results, state = State assessment results, susp = Suspension data, teacher = Teacher survey results

Table 31
Average Difference Score Across Questions Regarding Relevance of Data to Teacher Evaluation

question	A	B	C	E	F	H	I	J	K	ALL
t15rel2teacher_att	0.77	1.00	0.00	0.76	1.18	1.36	0.47	1.41	1.00	0.97
t15rel2teacher_bench	1.67	1.87	1.00	1.12	1.14	1.00	2.03	0.71	0.89	1.36
t15rel2teacher_dist	1.92	1.55	0.79	0.82	0.92	1.22	1.05	0.94	1.18	1.21
t15rel2teacher_el	1.58	1.41	0.79	0.76	1.27	0.79	1.60	1.00	1.34	1.22
t15rel2teacher_parent	0.84	1.10	0.79	0.96	0.78	0.79	0.82	1.27	1.26	0.95
t15rel2teacher_state	1.41	1.48	1.00	0.87	1.03	0.94	1.73	1.00	1.26	1.21
t15rel2teacher_susp	1.29	1.22	0.71	0.82	0.88	1.32	0.33	1.54	1.10	1.06
t15rel2teacher_teacher	1.00	1.45	1.22	0.87	1.86	1.22	1.33	1.17	1.10	1.31

Note: att = Attendance, bench = Teacher/site created assessments, dist = District assessments, el = English Learner language data, parent = Parent survey results, state = State assessment results, susp = Suspension data, teacher = Teacher survey results

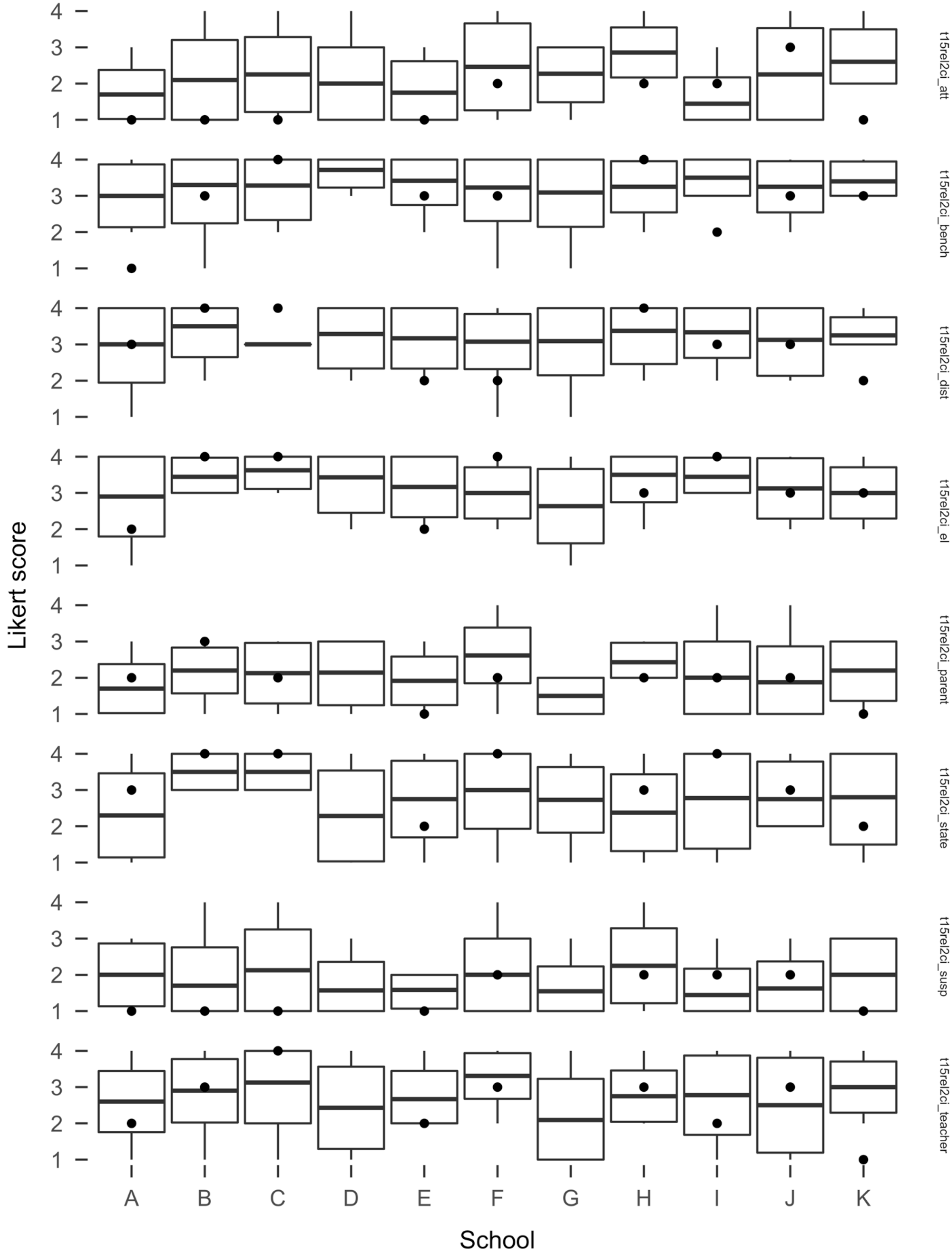

Figure 15. Plot of Teacher and Principal Responses Regarding Relevance of Data to Curriculum and Instruction

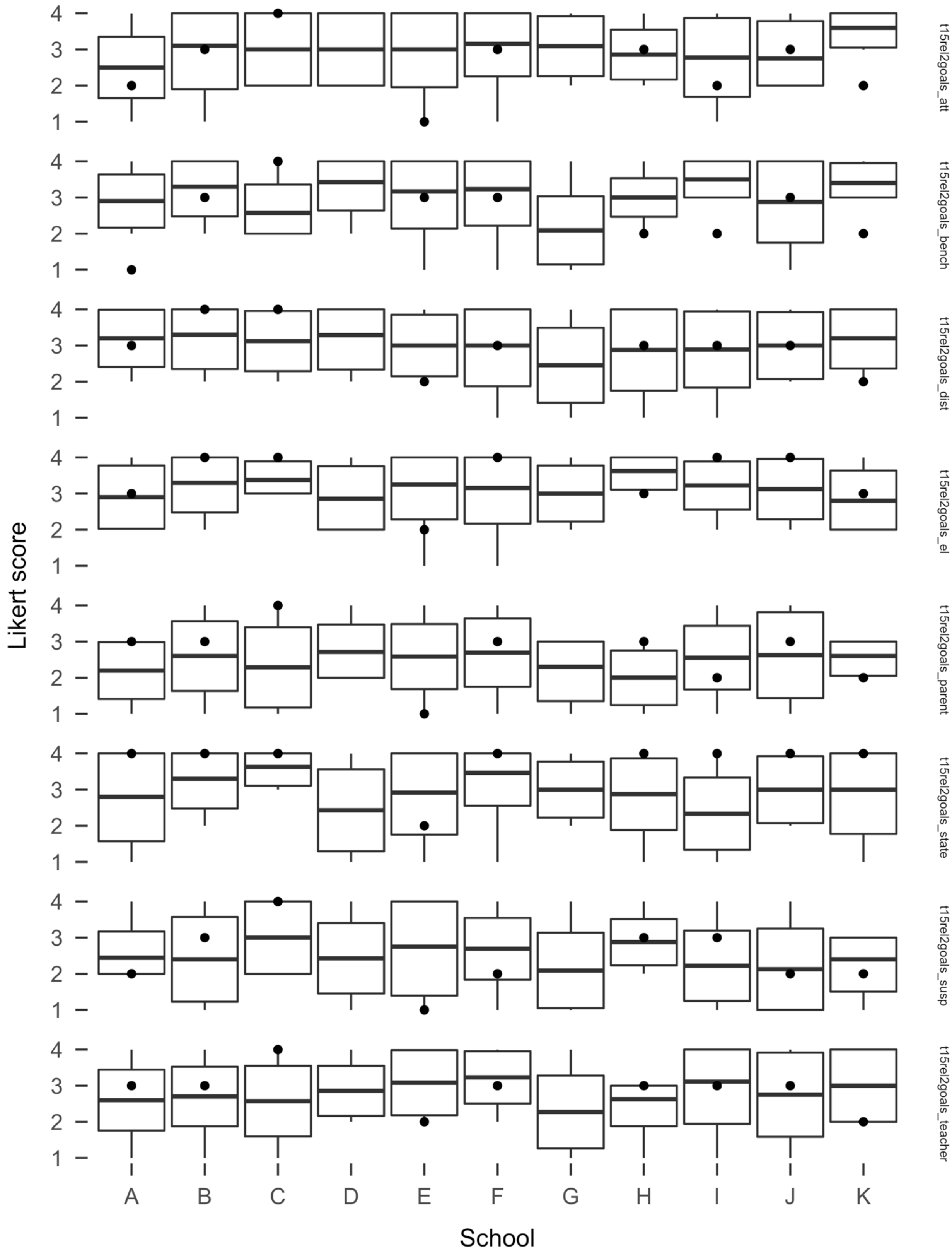

Figure 16. Plot of Teacher and Principal Responses Regarding Relevance of Data to School Goal Setting

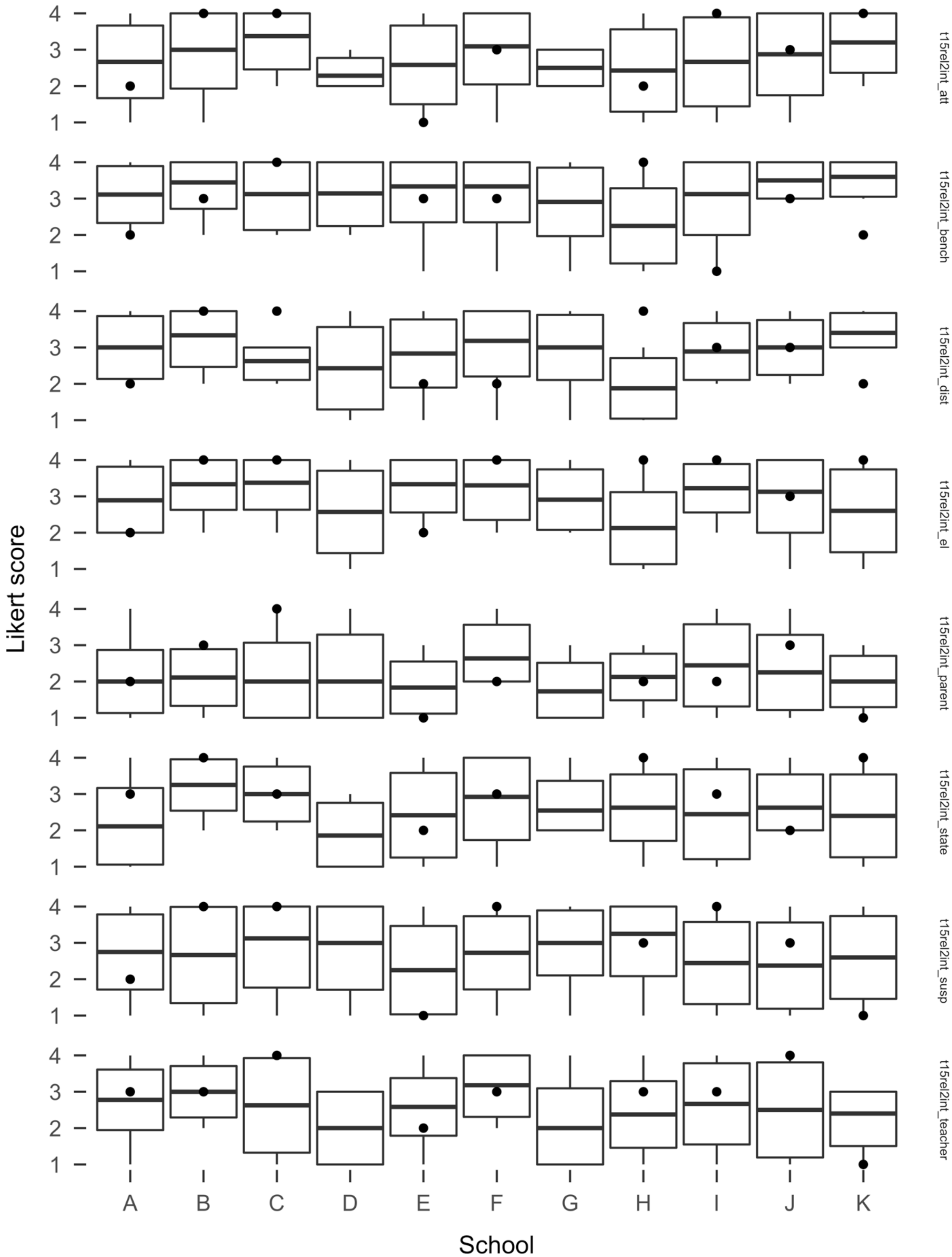

Figure 17. Plot of Teacher and Principal Responses Regarding Relevance of Data to Intervention

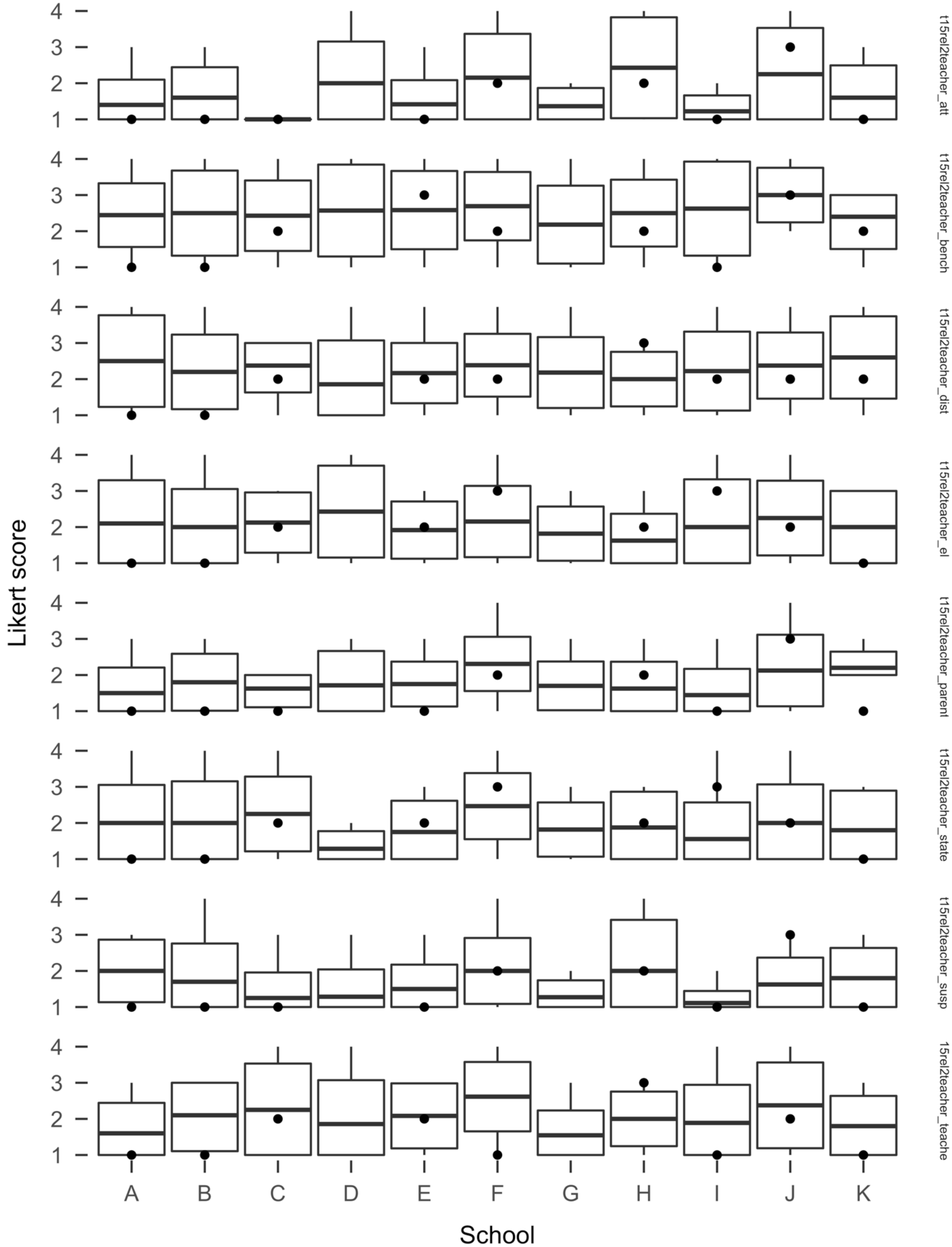

Figure 18. Plot of Teacher and Principal Responses Regarding Relevance of Data to Teacher Evaluation

Training and Support for Data-Driven Decision-Making

Principals and teachers were fairly well-aligned in regards to their responses regarding the setting in which training for data-driven decision-making occurred (Table 32/Figure 19). Difference scores were generally low across questions, and higher difference scores could be explained as a result missing principal data. Where there were differences between teacher and principal responses, principals tended to rate their credential programs as being more effective, as well as district level trainings as being more effective. One possible explanation for these differences is that the types of trainings offered to principals by their district might be different than those offered to teachers, and more effective or focused on the topic of data-driven decision-making.

Table 32
Average Difference Score Across Questions Regarding Training

question	A	B	C	E	F	H	I	J	K	ALL
t16train_collab	0.71	0.95	0.71	1.41	0.85	1.32	0.82	0.67	0.77	0.96
t16train_conf	0.89	0.77	0.71	1.04	1.96	2.03	1.00	0.82	0.89	1.27
t16train_cred	1.00			1.08	1.44	1.77	1.11	0.82		1.24
t16train_distsd	0.71	0.77	0.71	1.41	1.63	1.27	0.75	0.88	1.00	1.12
t16train_sitesd	0.84	0.89	0.87	1.04	0.80	1.37	0.58	1.15	1.26	0.98
t16train_under	1.10	0.95		1.00	2.12	0.79	1.41			1.37
ALL	0.89	0.87	0.75	1.18	1.55	1.48	0.98	0.88	1.00	

Note: No score was computed for certain questions due to principals not responding to those questions

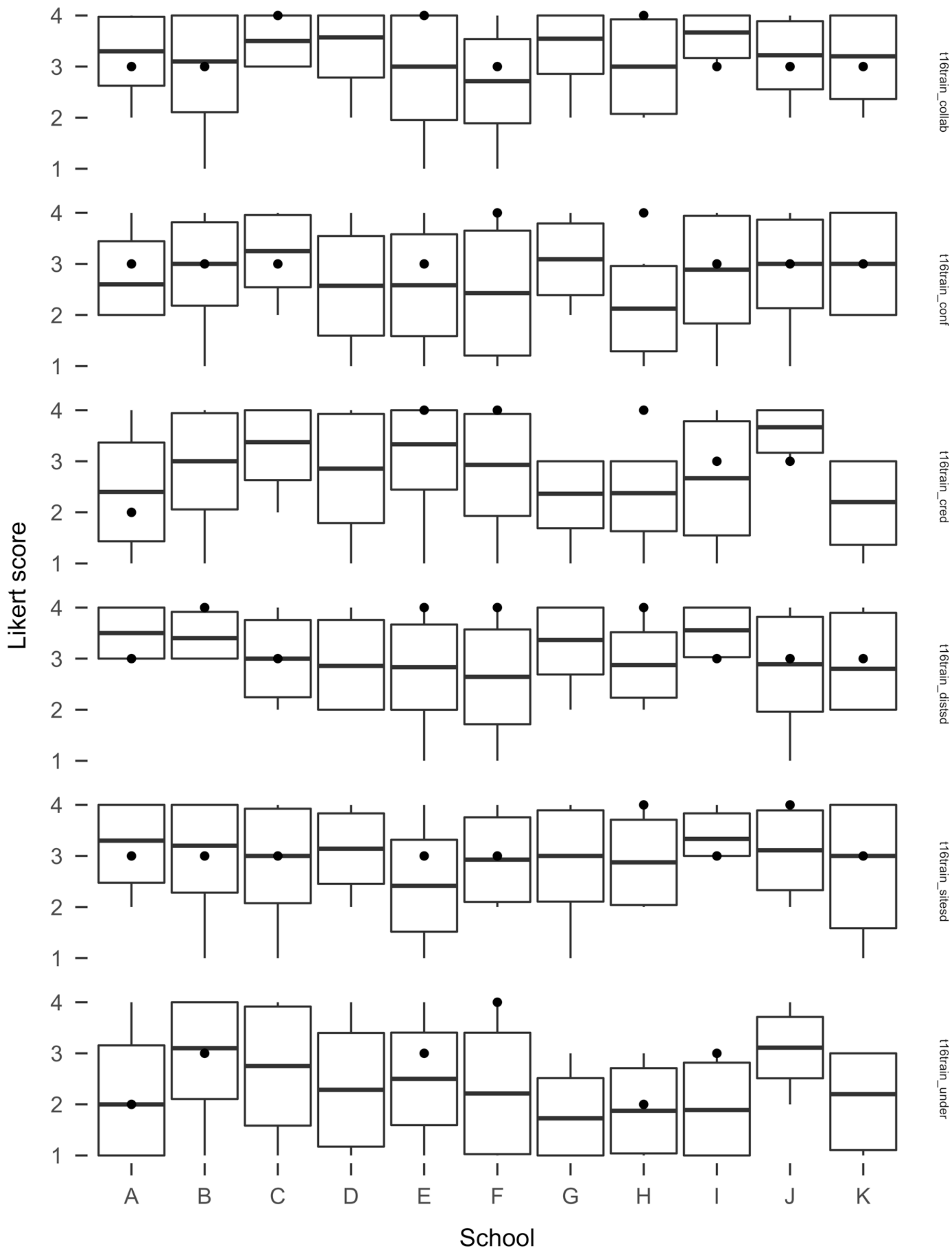

Figure 19. Plot of Teacher and Principal Responses Regarding Training for Data Driven Decision Making

Principal Leadership Style and Expectations

The questions regarding principal leadership style and expectations resulted in some interesting observations (Table 33/Figure 20). As far as principal style is concerned, most teachers rated their principals as having had a high level of distributed leadership. The accompanying difference scores show that principals are aligned strongly with the behaviors associated with distributed leadership, with principals selecting almost all fours or fives when describing their style. In fact, any principal responses outside of the one standard deviations of the teacher's responses tended to be above the teacher's responses, not below.

As for principal expectations (Table 34/Figure 21), every single principal except for one rated themselves a five, corresponding to the highest expectations for teachers in terms of data-driven decision-making. The remaining principal at school B rated themselves a one, which possibly indicates that the principal did not understand the scale. The oddness of this rating is amplified when considering that the school had the highest average rating by teachers in terms of principal expectations for data-driven decision-making, adding more credibility to the possibility of a misunderstood scale.

Table 33
Average Difference Score Across Questions Regarding Principal Leadership Style

question	A	B	C	E	F	H	I	J	K	ALL
t19style_account	1.00	1.14	1.37	0.91	0.96	0.79	0.94	1.73	1.22	1.12
t19style_finance	1.52	1.34	1.22	1.32	1.00	1.22	0.67	1.87	2.24	1.36
t19style_goals	1.18	1.26	1.00	1.00	1.15	0.61	0.82	1.17	0.71	1.04
t19style_inst	1.34	0.84	0.35	1.00	0.71	1.12	0.75	1.06	2.12	1.03
t19style_pdplans	1.41	1.14	1.54	0.87	0.82	0.61	1.33	1.62	2.12	1.25
t19style_vision	1.05	1.10	1.06	1.04	1.08	0.79	0.94	1.37	1.41	1.08
ALL	1.26	1.15	1.15	1.03	0.96	0.89	0.93	1.50	1.73	

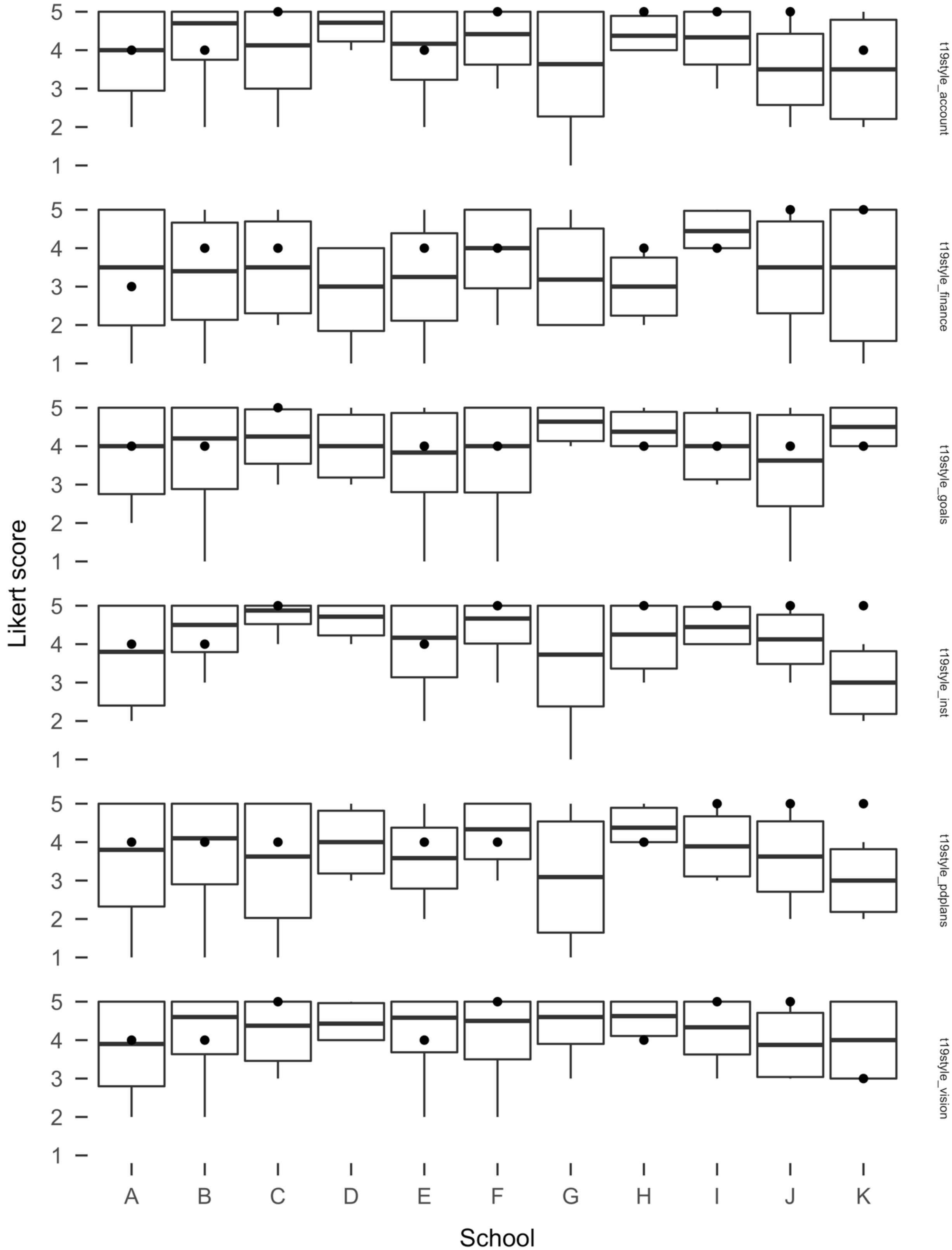

Figure 20. Plot of Teacher and Principal Responses Regarding Principal Leadership Style

Table 34
Average Difference Score On Question Regarding Principal Expectations for DDDM

question	A	B	C	E	F	H	I	J	K	ALL
t18prinex	2.24	3.73	2.00	1.68	1.41	1.54	3.02	2.89	2.00	2.39

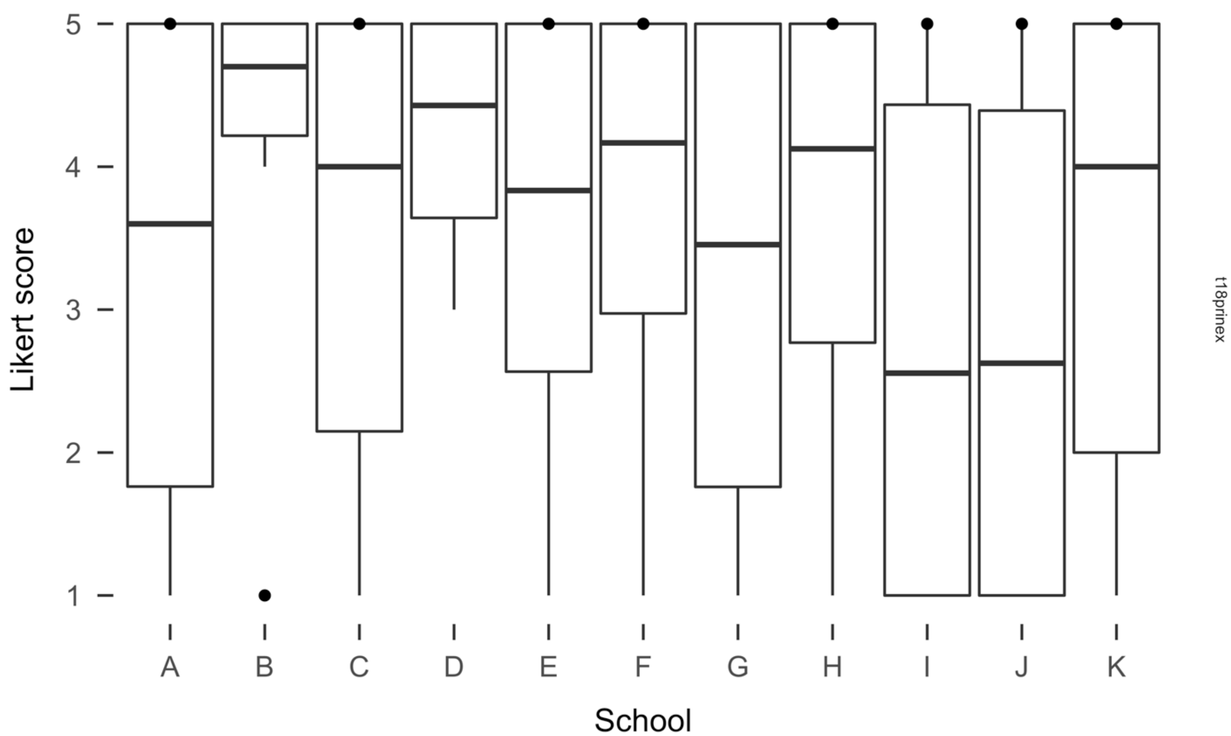

Figure 21. Plot of Teacher and Principal Responses Regarding Principal Expectations

Principal Leadership Behaviors

The set of questions on principal leadership behaviors have some of the higher difference scores seen across all questions in the survey (Table 35/Figure 21). The source of these higher differences seems to be similar to that of the previous questions on principal leadership style and expectations: principals have a tendency to rate themselves as engaging in these behaviors more often than teachers are rating them. This trend in principal overrating is exacerbated by the finding that teachers are not rating principals as high on average as they did on the questions regarding leadership style. This combination of lower teacher ratings and higher principal self-reported behaviors is resulting in the large differences seen below.

Table 35
Average Difference Score Across Questions Regarding Principal Leadership Behaviors for DDDM

question	A	B	C	E	F	H	I	J	K	ALL
t20behavior_connect	1.41	2.10	1.37	1.58	1.94	1.46	1.46	0.94	0.71	1.57
t20behavior_demonstrate	1.26	1.22	1.77	1.58	1.80	0.50	1.49	1.00	0.50	1.39
t20behavior_dialogue	1.18	1.52	1.58	1.53	2.06	0.79	0.67	0.87	0.87	1.38
t20behavior_feedback	1.14	1.30	1.62	1.38	2.22	0.93	1.60	0.79	2.12	1.52
t20behavior_lead	1.38	0.95	1.17	1.38	1.44	1.27	1.25	1.06	0.50	1.24
t20behavior_past	1.22	1.67	1.77	1.55	2.25	1.37	0.67	1.84	1.00	1.60
t20behavior_time	1.34	0.89	1.27	1.50	1.76	0.79	0.82	1.73	0.50	1.31
ALL	1.28	1.43	1.52	1.50	1.94	1.07	1.19	1.24	1.04	

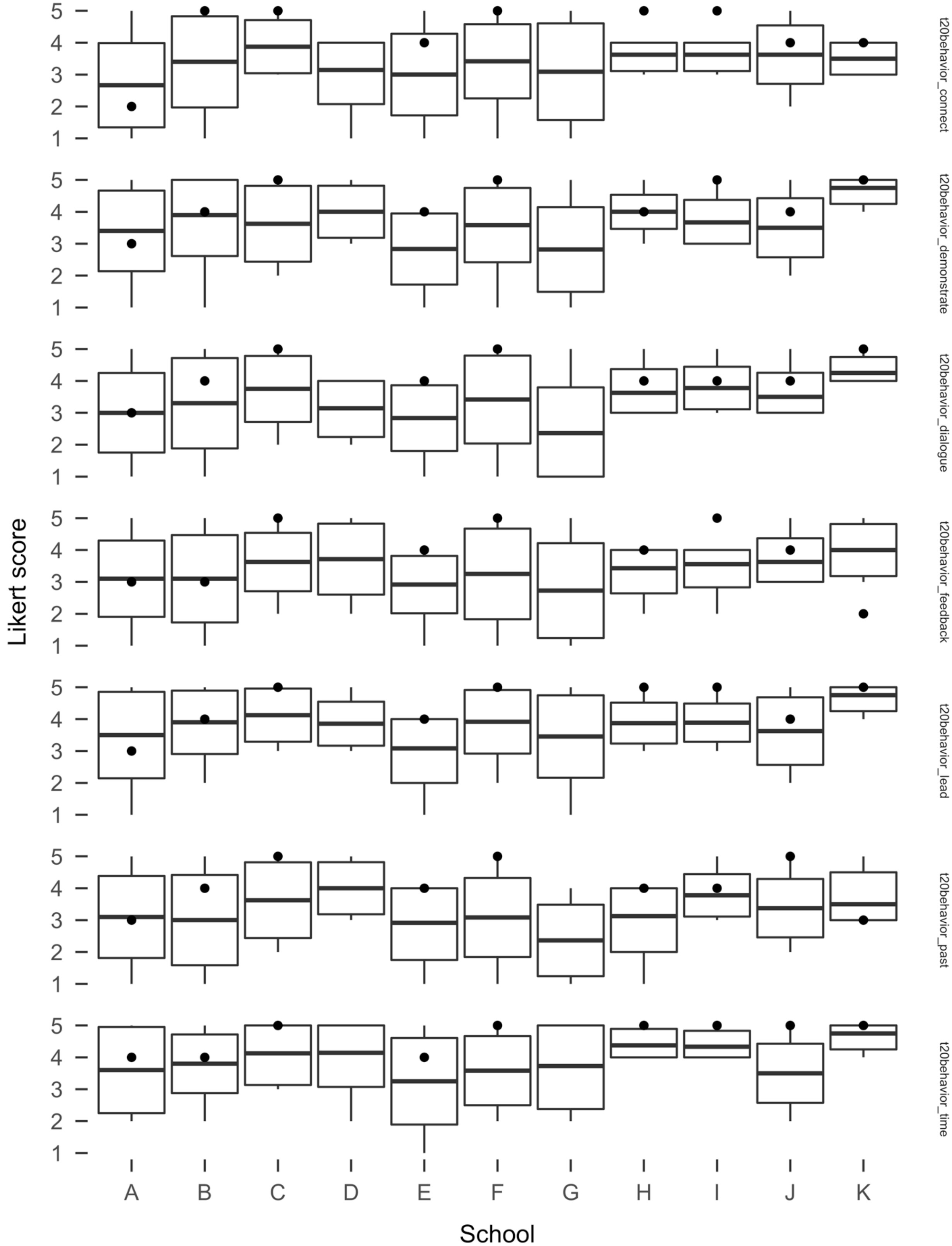

Figure 22. Plot of Teacher and Principal Responses Regarding Principal Behaviors in Data-Driven Decision-Making

District Leadership Expectations and Supports for Data Driven Decision Making

For the questions regarding district expectations for data-driven decision-making (Table 36/Figure 23), schools tended to fall in the middle of the range regarding their perceptions of district expectations. Schools A, H and K did report higher than average responses. Principals almost uniformly (with one exception) rated district expectations at a four, not five, the maximum level of expectations possible. Only six of nine principals responded to this item, indicating either fatigue, or possible discomfort at answering the question.

As compared to principal leadership behaviors, teachers and principals were more aligned in their responses regarding district supports for data-driven decision-making and district expectations for data-driven decision-making (Table 37/Figure 24). Unlike some of the other survey questions, when considering district supports, there isn't a clear direction in which principal perceptions of district support differ from teacher perceptions. On the whole, teacher responses are lower on the district measures than the principal measures, possibly indicating a perception of less support from the district. These trends are also evident in the response of the principals, as principals are also trending lower on the six questions regarding district support as compared to evaluating their own behaviors.

Table 36
Average Difference Score on Question Regarding District Expectations for DDDM

question	A	B	C	E	F	H	I	J	K	ALL
t21distexpect	2.78	1.58	1.67	1.41	1.53			1.34		1.77

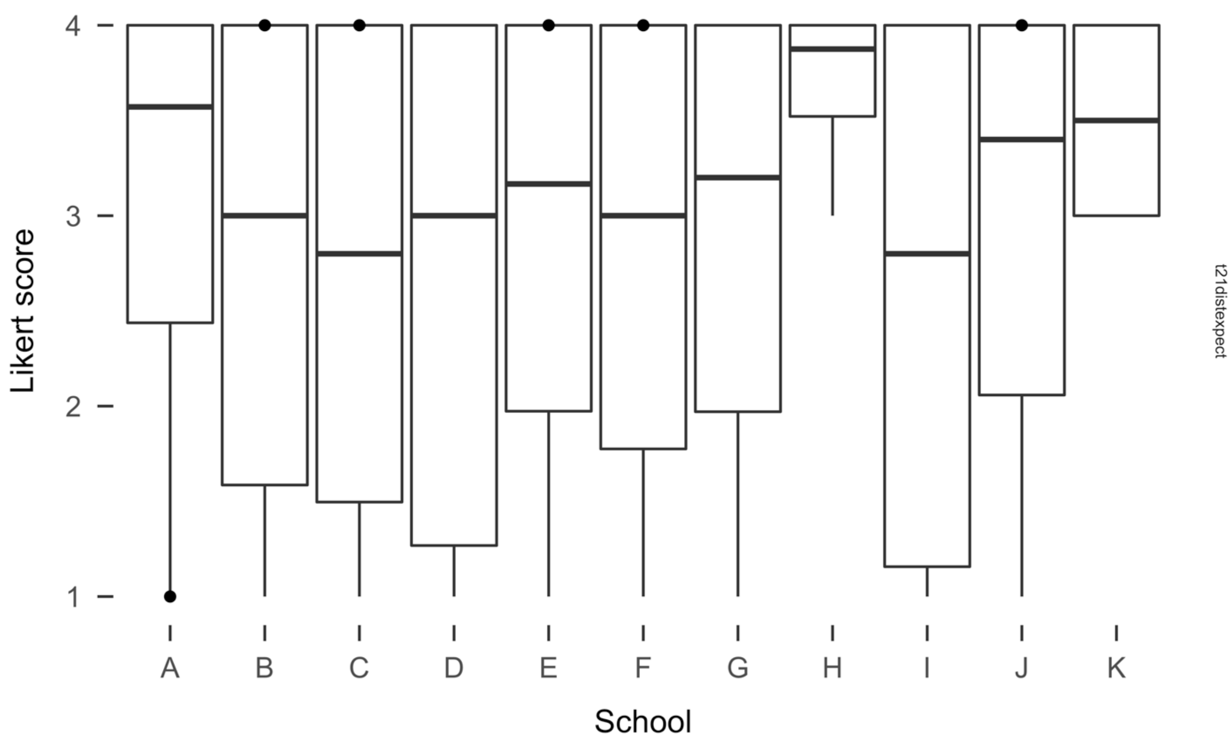

Figure 23. Plot of Teacher and Principal Responses Regarding District Expectations for Data-Driven Decision-Making

Table 37
Average Difference Score Across Questions Regarding District Leadership Supports for DDDM

question	A	B	C	E	F	H	I	J	K	ALL
t22distsupp_collect	0.95	0.84	1.46	1.35	1.47	1.50	1.54	0.94	1.00	1.27
t22distsupp_expectations	1.14	1.38	1.77	1.38	1.76	2.55	1.27	1.37	1.50	1.61
t22distsupp_expertise	1.00	1.48	1.70	0.87	1.55	0.61	0.87	2.32	2.40	1.45
t22distsupp_pd	0.95	0.84	1.32	1.50	1.55	1.77	1.17	1.62	1.58	1.38
t22distsupp_tools	1.18	0.95	1.46	1.15	1.22	0.79	1.41	1.32	1.87	1.24
ALL	1.05	1.13	1.55	1.27	1.52	1.60	1.27	1.58	1.73	

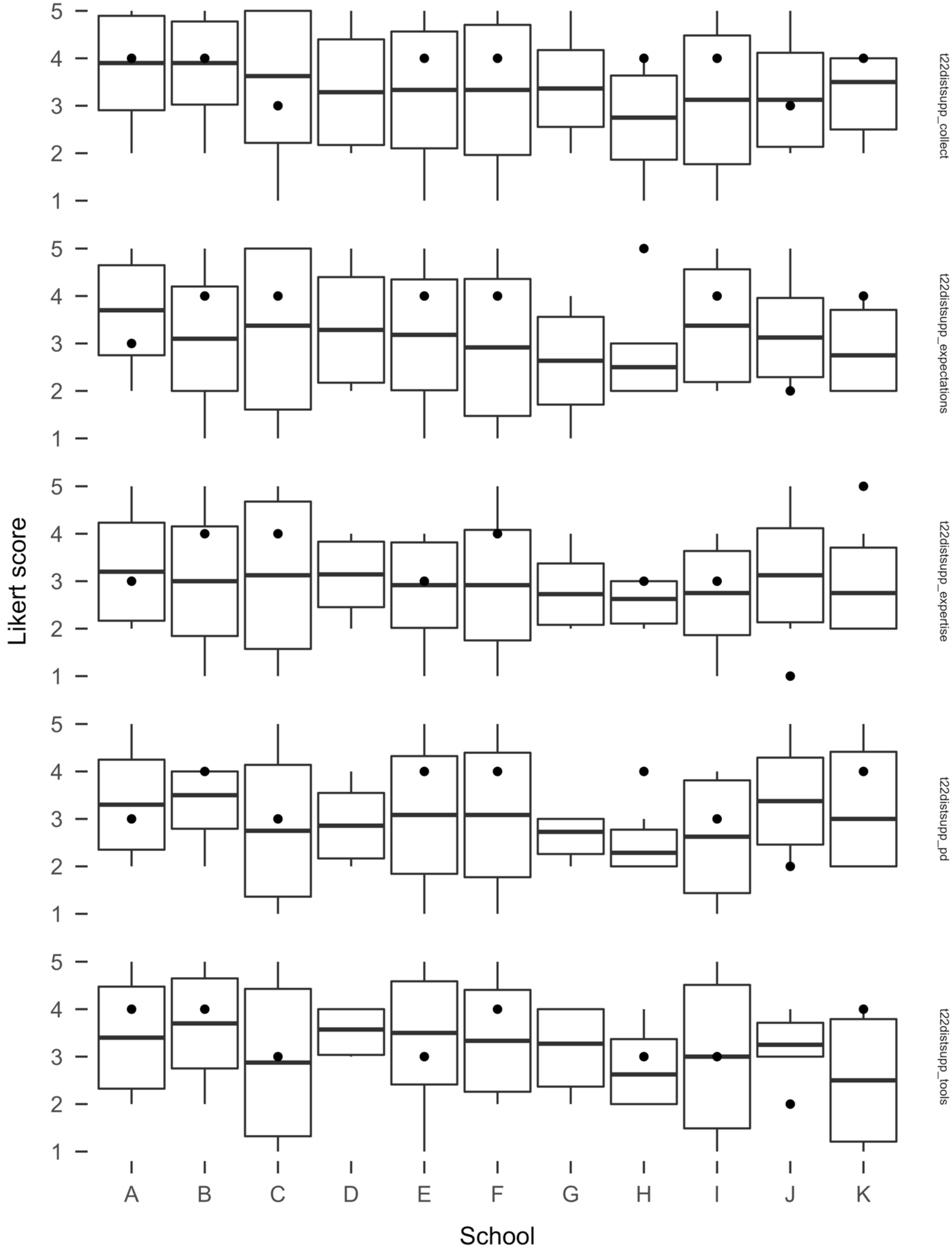

Figure 24. Plot of Teacher and Principal Responses Regarding District Support for Data-Driven Decision-Making

Teacher Behaviors in Using Student Data

Finally, when teachers rated their own frequency of data-driven decision-making behaviors, the variation from principals tended to be some of lowest among all of the survey question groups (Table 38/Figure 25). One interpretation is that teachers and principal may be more well aligned in their perceptions of teacher behaviors in data-driven decision-making. However, it is also important to consider that this trend may be a result of the ratings averaging relatively high for teachers. Principals with similarly high ratings would be more likely to align with their teachers. When considering outliers for principals in rating teacher behaviors, principal perceptions tended to err on the lower side of the range of teacher responses, indicating a pattern on this question of principals underestimating the extent of behaviors as compared with their teachers. In addition, it seems to be a trend that individuals estimate that others engage in desirable behaviors less than others self-report.

Table 38
Average Difference Score Across Questions Regarding Teacher Behaviors In DDDM

question	A	B	C	E	F	H	I	J	K	ALL
t17freq_aggregate	1.00	1.22	0.61	0.82	1.36	0.79	1.56	0.61	0.71	1.06
t17freq_classgoals	1.41	0.84	0.50	0.91	1.04	1.32	1.56	0.71	2.65	1.22
t17freq_indgoals	1.48	0.89	0.50	0.87	0.71	0.50	1.00	1.66	0.87	1.01
t17freq_indstud	1.55	0.89	0.61	0.76	0.78	0.71		0.94	0.50	0.92
t17freq_inter	1.55	1.14	0.35	0.87	0.39	0.00	0.87	0.50	1.00	0.87
t17freq_smallgroup	0.77	1.00	0.35	0.76	0.78	1.12	1.73	0.35	0.50	0.93
t17freq_whole	1.55	0.89	0.61	0.76	0.73	1.12	1.00	0.87	1.50	1.01
ALL	1.36	0.99	0.52	0.82	0.87	0.90	1.34	0.90	1.31	

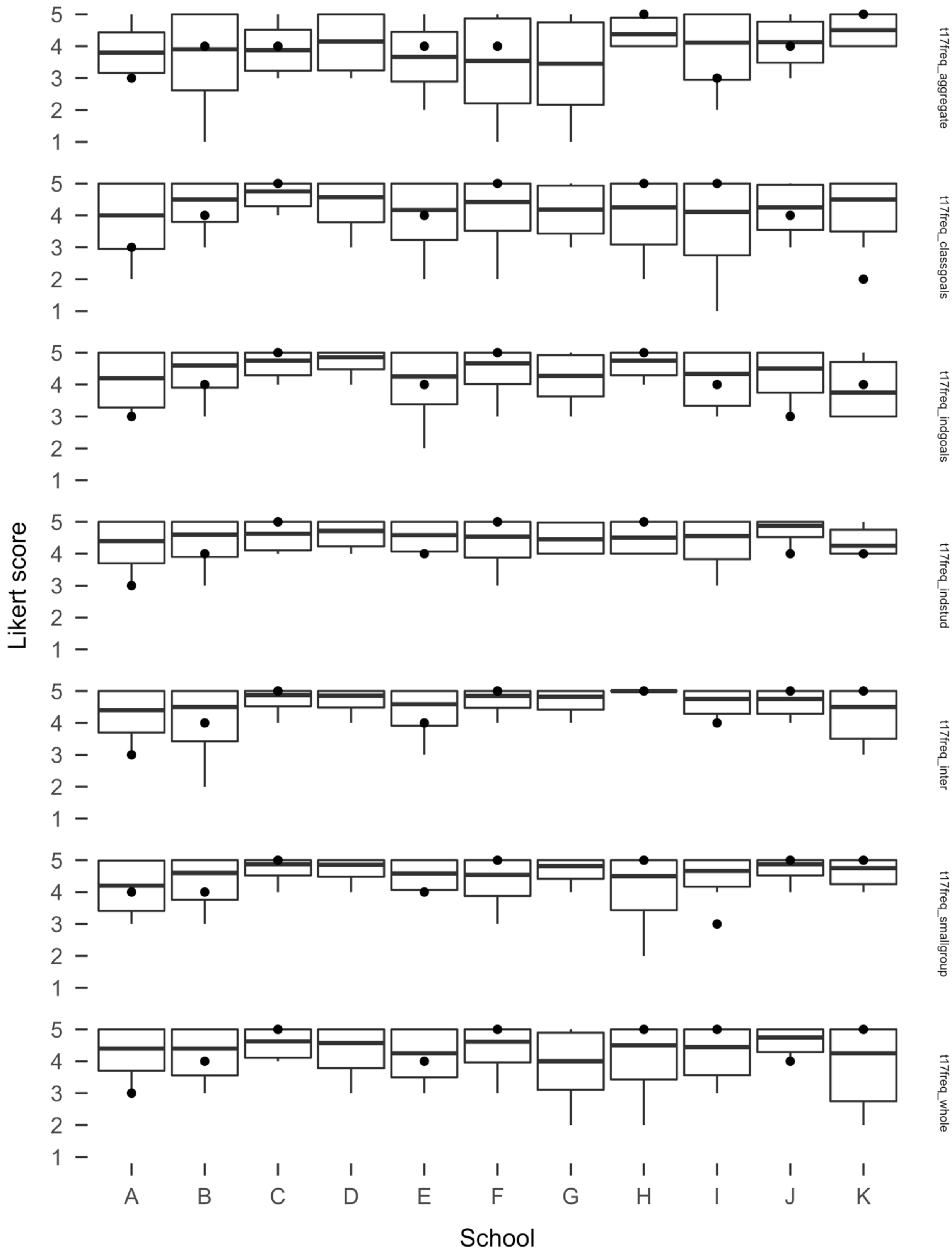

Figure 25. Plot of Teacher and Principal Responses Regarding Teacher Behaviors in Data-Driven Decision-Making

Relationships Between Variables

Having analyzed the variables within their own question groups, the next step was to get a greater understanding of the relationships among groups of survey questions. This occurred through several steps. First, I performed a series of confirmatory factor analyses within each groups of survey questions to determine if there was an underlying construct that could represent those groups. Second, I performed a simple transformation of survey questions into a single composite score representing survey question groups, and then analyzed the correlations across those composite scores. Next, I performed a correlation analysis of individual survey items with the seven teacher behavior outcome survey questions. These items were selected in part based upon the original descriptive survey analysis. Third, utilizing information from the correlation analyses and confirmatory factor analyses I specified a structural model, using those variables identified as suitable to include in the model. Finally, I generated factor scores from the structural model. These factor scores were then used in a hierarchical model in order to investigate the school level effects on the intercept for the regression portion of the structural model.

Latent Variables

All of the clusters of questions were analyzed with a Confirmatory Factor Analysis utilizing the *lavaan* package in R to determine if the survey questions described underlying constructs. A polychoric correlation table was generated for each group of survey questions and is available in Appendix D. Due to the ordinal nature of the data, the *ordered* setting was set to true, resulting in the use of the diagonal weighted least squares estimator (DWLS), instead of the normal maximum likelihood estimator. The summary of the results of this analysis are in Table 39. The first set of models were regarding differing dimensions of the eight data types used throughout the survey, including difficulty of access to data, frequency of use, expertise in use, and relevance of data. The analyses did not support the notion of a generalized underlying factor across multiple types of data. This is likely due to the variation between teachers in how differing types of data are viewed, as exemplified by the disparity on multiple measures between survey data, and site assessments, for example. The one exception to this trend was the underlying possible construct of relevance of data to teacher evaluation with a CFI of 1.000 and RMSEA of 0.000. However, this result is likely due to the underlying distaste among teachers for using any sort of data for teacher evaluation.

Table 39
Summary of Fit for CFA Between Groups of Questions on Data Types

Model	Items	$\chi2$	df	p	CFI	TLI	RMSEA	P-value RMSEA ≤ 0.05
Difficulty of access to Data	8	40.273	20	0.005	0.940	0.917	0.102	0.036
Frequency of Use of Data	8	41.128	20	0.004	0.742	0.639	0.103	0.031
Expertise in Use of Data	8	50.428	20	0.000	0.913	0.878	0.123	0.004
Relevance of Data to Site Goals	8	56.678	20	0.000	0.873	0.822	0.140	0.001
Relevance of Data to Teacher Evaluation	8	12.435	20	0.900	1.000	1.028	0.000	0.969
Relevance of Data to Curriculum and Instruction	8	47.272	20	0.001	0.742	0.639	0.123	0.007
Relevance of Data to Intervention	8	85.580	20	0.000	0.611	0.455	0.192	0.000

The remaining measures from the teacher survey were tested for underlying factors (Table 40), and all seemed to demonstrate a positive set of fit statistics. The frequency of teachers engaging in data-driven decision-making behaviors across multiple dimensions seem to support a generalized sense of data-driven decision-making, while principal style, principal behaviors, and district supports also seem to represent generalized notions of those constructs. The underlying factors are preferable because they could result in a more parsimonious model with less paths to fit. One drawback of these factors, however, is that the model will lose the nuance in understanding how differing district supports and principal behaviors results in particular changes in differing types of teacher behavior. Finally, principal style does seem to be a group of questions that can readily remain as a factor.

Table 40
Summary of Fit for CFA Between Groups of Questions on Supports, Behaviors, and Styles

Model	Items	$\chi 2$	df	p	CFI	TLI	RMSEA	P-value RMSEA ≤ 0.05
Frequency of Teachers Engaging in DDDM Behaviors	6	11.877	14	0.616	1.000	1.016	0.000	0.799
Principal Style	6	1.676	9	0.996	1.000	1.044	0.000	0.998
Principal Behaviors	7	2.665	14	1.000	1.000	1.024	0.000	1.000
District Supports	5	1.313	5	0.934	1.000	1.023	0.000	0.959

Correlations Across Survey Question Groups

I next created a composite score for purposes of performing a correlation analysis. This composite score was the mean of all answers provided by a subject for that particular group of survey questions, with missing responses dropped in calculating the means for each question group. These means were then used to generate a table of correlations between the groups of questions with a composite score, as well as with the individual questions describing the expectations of both the principal as well as district leadership in regards to data-driven decision-making. While the factor analysis had several groups of questions demonstrate a poor fit, these composite scores still might provide evidence to then inspect the relationship of individual questions with other individual questions. These correlations are available in Table 41.

Table 41

Correlation of Composite Variables Across Full Survey

	t11often	t12diff	t13expert	t15rel2ci	t15rel2goals	t15rel2int	t15rel2teacher	t16train	t17freq	t18_prinex	t19style	t20behavior	t21distexpect	t22distsupp
t11often	1.00													
t12diff	0.39	1.00												
t13expert	0.16	0.30	1.00											
t15rel2ci	0.29	0.40	0.18	1.00										
t15rel2goals	0.31	0.27	0.08	0.67	1.00									
t15rel2int	0.34	0.26	0.06	0.67	0.61	1.00								
t15rel2teacher	0.20	0.34	-0.04	0.57	0.36	0.48	1.00							
t16train	0.26	0.25	0.21	0.35	0.24	0.34	0.20	1.00						
t17freq	0.17	0.23	0.18	0.37	0.31	0.14	0.22	0.38	1.00					
t18_prinex	0.09	0.20	0.06	0.09	0.06	0.00	0.06	0.20	-0.16	1.00				
t19style	0.11	0.38	0.01	0.43	0.35	0.28	0.24	0.21	0.15	0.13	1.00			
t20behavior	0.17	0.23	0.09	0.38	0.20	0.15	0.25	0.29	0.30	0.00	0.73	1.00		
t21distexpect	0.09	-0.02	0.09	0.03	-0.04	0.15	0.24	0.15	0.02	0.18	0.00	0.06	1.00	
t22distsupp	0.24	0.25	0.07	0.38	0.41	0.31	0.31	0.33	0.28	0.05	0.37	0.38	0.02	1.00

Note: t11often = How often different types of data are used, t12diff = The difficulty in gaining access to different types of data, t13expert = Teachers reported expertise in using different types of data, t18prinex = Principal expectations, t15rel2ci = Relevance to curriculum and instruction of different types of data, t15rel2goals = Relevance to site wide goal setting of different types of data, t15rel2int = Relevance to intervention of different types of data, t15rel2teacher = Relevance to teacher evaluation of different types of data, t16train = Amount of training received for data use in different settings, t17freq = Frequency of teacher data-driven decision making behaviors, t19style = Principal distributed leadership style, t20behavior = Principal data-driven leadership behaviors, t21distexpect = District expectations for data-driven decision-making, t22distsupp = Amount of district support provided for data-driven decision-making

When analyzed, the correlations table suggest some relationships between groups of question. Overall, most question groups had a weak to moderate correlation with each other of no more than 0.5, with a few exceptions. This is not surprising considering the mixed results from the confirmatory factor analysis. One notable exception to this trend were the relevance question groups, many of which had a correlation of above 0.5 with each other. The other important exception to this trend in correlations was the relationship between principal leadership behaviors, and principal leadership style. There was a 0.73 correlation between these two principal measures, which demonstrated a positive and strong relationship between increased principal behaviors in supporting data driven decision making, and a distributed leadership style.

On the other hand, some other relationships did not manifest which might be expected. For example, expertise was only weakly correlated with amount of training received in data-driven decision making, with a correlation of 0.21. In another example, principal expectations and district expectations were also weakly correlated, with a 0.18 correlation showing a lack of connection between teacher perceptions of principal and district expectations for DDDM. This may hint at a deeper lack of alignment between site and district leadership, but there is not enough information to evaluate this possibility further.

As for teacher frequency in engaging in data-driven decision-making behaviors, the outcome variable of interest for this survey, relationships with the other survey groups informed which survey questions would be most appropriate for using in the structural model. Using a cutoff of a correlation of 0.25 between teacher behaviors and the other survey groups as a starting point for the eventual model, some question groups are dropped from ultimate consideration. For example, the question groups relating to the frequency of use, difficulty in access to data, and expertise in data use have a lower correlation with the teacher behavior composite score. Two of the relevance of data composites scores also fall below r = 0.25, while relevance to curriculum and instruction (r = 0.37) and relevance to school goals (r = 0.31) show a stronger correlation. Amount of teacher training (r = 0.38), principal behaviors (r = 0.30) and district supports (r = 0.28) round out the remaining groups of questions meeting this cutoff of r = 0.25. Interestingly, both principal (r = -0.16) and district expectations (r = 0.02) do not meet the threshold. It would seem that higher expectations on their own don't seem to have much of a connection to teacher behaviors in data-driven decision making. Finally, principal leadership style doesn't seem to have a direct relationship to teacher behaviors (r = 0.15), but the strong correlation to principal behaviors may justify its continued inclusion in the eventual structural model.

Given the correlations observed between the composite scores for relevance and teacher behavior outcomes, I decided to generate the predicted factor scores for teacher behavior from the Confirmatory Factor Analysis and calculate a biserial correlation between the individual question responses and that factor score. The results are available below in table 42. Only certain data types had more than a weak correlation between the teacher perception of relevance and frequency of teacher behaviors. For purposes of the structural equation model, relevance survey items regarding EL data, district assessments, and site benchmark data with a correlation greater than 0.20 will be included based upon the correlations I observed in the table.

Table 42
Biserial correlations between factor score for teacher behavior frequency and survey question responses for relevance

Survey question	Correlation to Teacher Factor
t15rel2goals_state	0.00
t15rel2teacher_state	0.10
t15rel2ci_state	0.04
t15rel2int_state	-0.08
t15rel2goals_el	0.30
t15rel2teacher_el	0.28
t15rel2ci_el	0.29
t15rel2int_el	0.02
t15rel2goals_dist	0.49
t15rel2teacher_dist	0.21
t15rel2ci_dist	0.13
t15rel2int_dist	0.10
t15rel2goals_bench	0.36
t15rel2teacher_bench	0.28
t15rel2ci_bench	0.45
t15rel2int_bench	0.27
t15rel2goals_susp	0.09
t15rel2teacher_susp	0.21
t15rel2ci_susp	0.22
t15rel2int_susp	-0.02
t15rel2goals_att	0.05
t15rel2teacher_att	0.29
t15rel2ci_att	0.21
t15rel2int_att	0.01
t15rel2goals_parent	0.03
t15rel2teacher_parent	0.08
t15rel2ci_parent	0.21
t15rel2int_parent	0.04
t15rel2goals_teacher	0.08
t15rel2teacher_teacher	0.02
t15rel2ci_teacher	0.17
t15rel2int_teacher	0.06

Correlations Between Survey Items

I next performed a polychoric correlation analysis between a subset of the individual survey items (Table 43). While the composite correlation analysis can provide a generalized indication regarding the survey question areas and their relationships to teacher behaviors in data-driven decision-making, the individual item analysis can provide some additional detail as to what specific conditions are related to individual teacher data behaviors. Overall, these correlation results should not be considered to be conclusive evidence of a causal relationship. However, at the least, a higher correlation suggests a possibility of a relationship to teacher behaviors. These correlations were mostly positive. Considering the large number of correlations represented on this table, a few negative correlations are probably more indicative of random variation, not actual inverse relationships.

Table 43

Polychoric Correlation of Individual Questions With Teacher Outcome Questions

	indgoals	classgoals	aggregate	whole	smallgrou	indstud	inter
t16train_under	0.20	0.19	0.14	0.23	0.17	0.19	0.19
t16train_cred	0.20	0.31	0.09	0.28	0.22	0.23	0.16
t16train_distsd	0.14	0.16	-0.19	-0.04	0.05	0.41	0.08
t16train_conf	-0.06	-0.06	0.15	0.19	-0.03	-0.14	0.21
t16train_sitesd	0.18	0.15	0.02	0.19	0.15	0.22	0.25
t16train_collab	0.02	-0.05	-0.03	-0.01	0.02	0.07	0.13
t18prinex	0.02	0.08	-0.10	-0.02	-0.07	0.01	-0.14
t19style_vision	0.13	0.17	0.09	0.07	0.07	0.11	0.14
t19style_goals	0.09	0.25	0.23	0.24	0.13	0.13	0.19
t19style_inst	0.28	0.22	0.12	0.20	0.16	0.19	0.22
t19style_pdplans	0.11	0.15	0.17	0.31	0.05	0.10	0.10
t19style_finance	0.06	0.05	0.21	0.21	0.02	0.17	0.08
t19style_account	0.26	0.26	0.19	0.21	0.11	0.26	0.19
t20behavior_time	0.15	0.23	0.42	0.14	0.23	0.09	0.13
t20behavior_lead	0.13	0.23	0.29	0.26	0.12	0.11	0.18
t20behavior_demonstrate	0.13	0.21	0.37	0.33	0.13	0.13	0.10
t20behavior_feedback	0.11	0.18	0.35	0.33	0.15	0.23	0.13
t20behavior_dialogue	0.08	0.20	0.40	0.34	0.04	0.13	0.03
t20behavior_connect	0.07	0.16	0.31	0.22	0.10	0.18	0.02
t21distexpect	0.08	0.22	0.38	0.09	0.19	0.09	0.03
t22distsupp_expertise	0.21	0.16	0.18	0.31	0.07	0.20	0.12
t22distsupp_expectations	0.22	0.16	0.22	0.28	0.08	0.31	0.10
t22distsupp_tools	0.06	0.09	-0.01	0.06	0.04	0.15	0.06
t22distsupp_pd	0.17	0.13	0.18	0.15	0.03	0.21	0.01

Note: indgoals=Set individual student improvement goals and targets, classgoals=Set class improvement goals and targets, aggregate=Analyze aggregate data with other teachers, whole=Tailor instruction for the whole class, smallgrou=Divide students into small groups to provide interventions, indstu=Change instructional strategies for individual students, inter=Identify students to target for intervention

Training, like all of the other conditions supporting data-driven decision-making, had a mixed relationship to teacher DDDM behaviors. Undergraduate courses, conferences, site staff development, and collaboration had a weak relationship with all of the teacher behaviors. Credential classes had a stronger relationship with whole class related behaviors such as setting class goals and tailoring instruction for the whole class. Finally, district staff development had one of the strongest correlations of the whole analysis in its relationship with data use in changing instructional strategies for individual students. As for principal expectations, while most correlations across the entire table were fairly low (under 0.3), principal expectations were notably lower than that in their correlations to teacher behaviors. District expectations are similarly uncorrelated, with the exception that higher expectations are positively correlated ($r = 0.38$) with aggregate analysis of data.

Principal distributed leadership style is also weakly positively correlated across all teacher behaviors. Particularly notable is the relationship of leadership style with tailoring instruction for the whole class, especially as principals developed professional development plans jointly with their staff. One exception to principal leadership style and its influence on teacher behaviors was creating a shared vision. This item's correlations were notably lower than other correlations across principal style. Principal data-driven leadership behaviors had a mixed influence when considered across teacher behaviors. Individual and small group data-driven decision-making behaviors, such as setting individual goals, adjusting instruction for individuals or small groups, or identifying students for intervention, were very weakly correlated with principal behaviors. By comparison, some of the highest correlations of the survey were observed between all of the principal leadership behaviors and setting class goals, aggregate analysis, and tailoring instruction for the whole class. The most influential principal behaviors when considered across all teacher behaviors were engaging in dialogue regarding data-driven decision-making, demonstrating the process of DDDM, and providing feedback on teacher data practices.

Finally, district supports were not as strongly associated with teacher behaviors as principal behaviors. That being said, teachers tended to engage at a higher rate in the same group level data behaviors as in the principal sample (setting class goals, aggregate analysis, and tailoring instruction for the whole class) when the district provided expertise for sites in implementing DDDM, as well as setting expectations for data-driven decision-making.

Structural Models

Initial Model.

Based upon the initial group of correlations, I build a structural equation model to understand the relationship of principal behaviors, principal leadership style, district supports, previous training, and relevance of different data types such as English Learner data, district benchmarks, and site assessments. The diagram for this model is available below (Figure 26).

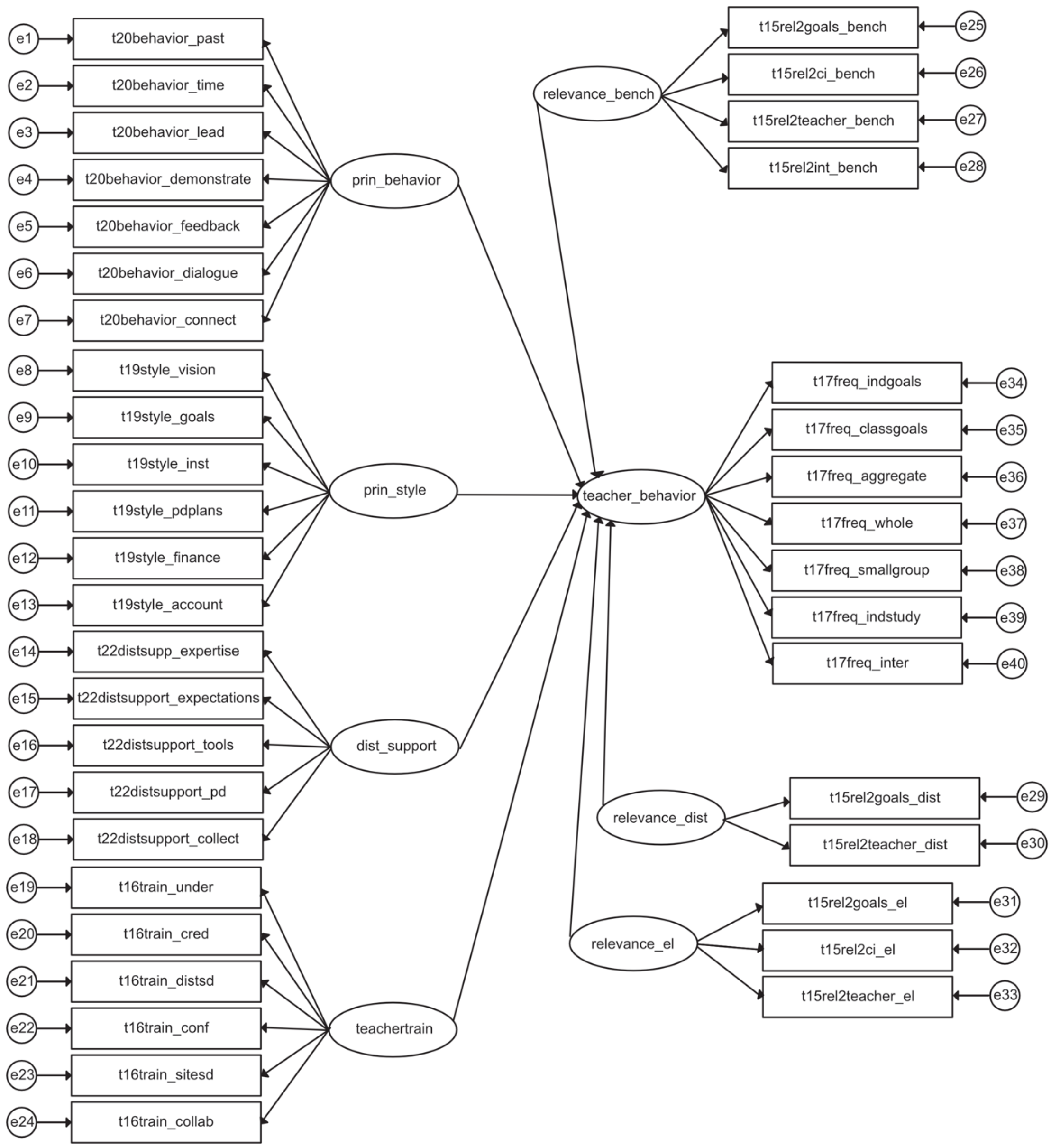

Figure 26. Structural equation diagram for Teacher Behavior Model

Note: Covariances are not noted on the path diagram due to the large number of covariances between latent factors. Covariances were estimated between all latent factors.

This model strips out many of the survey variables, such as frequency of use of data, ease of access to data, expertise in data, and principal and district expectations. These exclusions are due to initial correlation analysis indicating weak relationships to the outcome variable of interest: teacher behaviors. In addition, some groups of questions regarding relevance of data were removed due to the correlation analysis showing a lack of correlation with the teacher behavior outcome.

The model was estimated using the Diagonal Weighted Least Squares estimator in the *lavaan* package due to the presence of ordinal data, the same estimator used in the confirmatory factor analyses performed in the previous section. Only 86 of the 104 responses were included due to missing data. The goodness of fit statistics for this structural equation model were as follows: The RMSEA was 0.053 [0.041, 0.0.064], p = 0.323, CFI = 0.989, and TLI = 0.988. These fit statistics indicate a mixed fit for the model. CFI and TLI indicate a strong fit, but the RMSEA is out of the range of best fit of below 0.05. I will only share the regression results in table 44. All factor loadings were statistically significant, but the regression coefficients were not all statistically significant.

Table 44
Data-Driven Decision-Making Teacher Behavior Model - Regression Portion Only *(n = 86)*

	Estimate	Std. Err	Z-value	P(>|z|)	Std. Est.
Regressions					
teachfreq <-					
prinbehavior	0.983	0.480	2.046	0.041*	0.719
prinstyle	-0.914	0.448	-2.040	0.041*	-0.669
distsupport	0.063	0.255	0.247	0.805	0.046
teachertrain	0.306	0.181	1.689	0.091	0.224
relevance_el	0.475	0.313	1.515	0.130	0.347
relevance_dist	-0.085	0.237	-0.357	0.721	-0.062
relevance_bench	0.154	0.323	0.477	0.634	0.113

Note: * = 0.05, ** = 0.01, *** = 0.001

This initial model supports the theorized positive effect of principal leadership behaviors on teacher data-driven decision-making behaviors. In addition, due to the negative coefficient for principal style, the model also seems to support a more prescriptive leadership style as contributing towards an increase in teacher data-driven decision-making behaviors. However, there is a high covariance estimated by the model between these two factors ($r = 0.769$), which might be contributing towards the flipping of the sign on this coefficient as compared to the positive correlation between these two constructs. The remaining coefficients for the other factors are not statistically significant. Due to the lack of statistical significance of most of the included factors, I then fit another model removing many of the non-significant factors.

Final Model.

The limited sample size may have been a contributing factor towards the difficulty in finding statistical significance for many of the question groups identified by the correlation analysis as possibly related to teacher data-driven decision-making behaviors. I proceeded to develop a simpler structural equation model, omitting the relevance factors, as well as the teacher training factors. While the district support factor had a very low statistical significance, I believe it is still important to include district level supports in the final model, due to the role of district level supports in the theoretical framework, and as part of the research questions. The model used for this analysis is available below in figure 27.

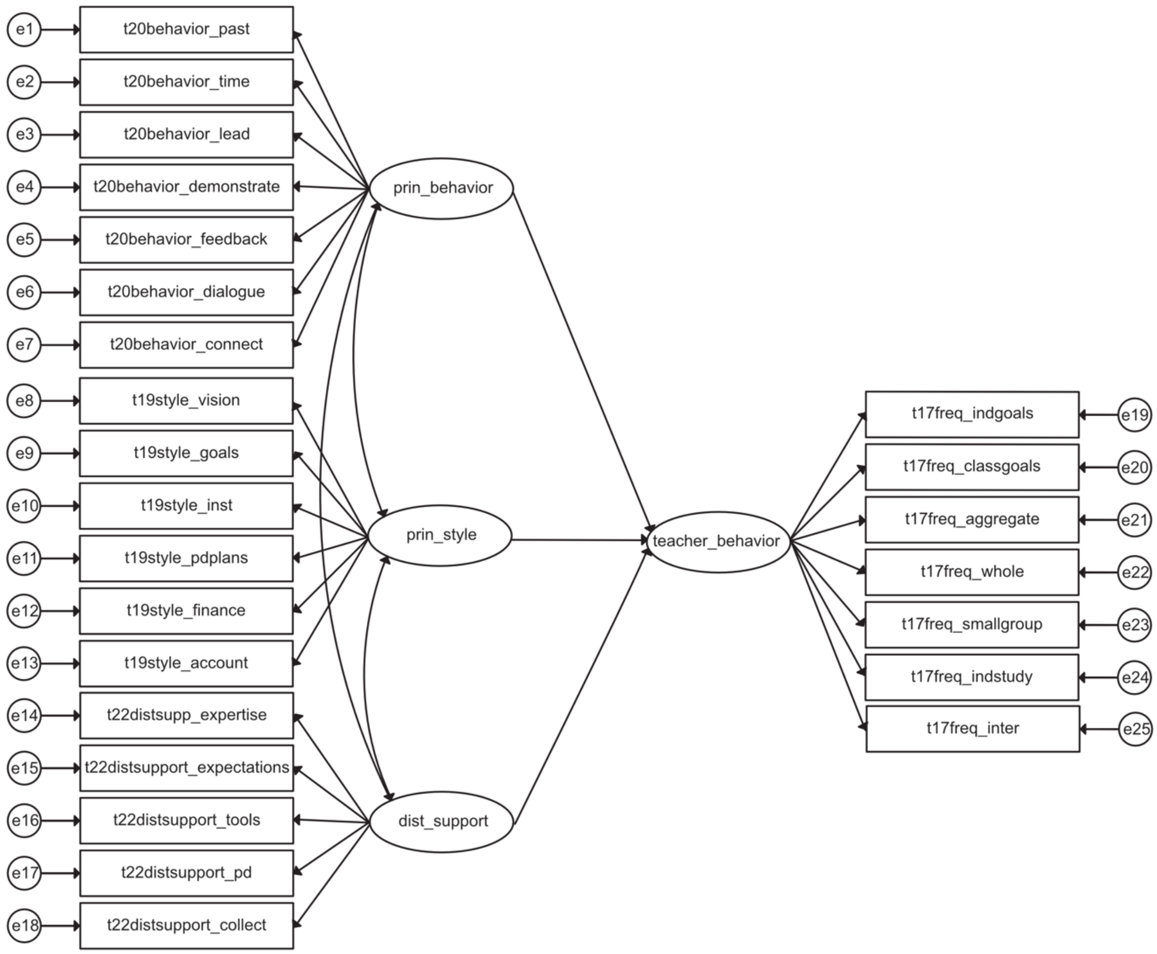

Figure 27. Structural Equation Model Path Diagram for Final Teacher Behavior Model

The model was also estimated using the Diagonal Weighted Least Squares estimator in the *lavaan* package. Missing data reduced the sample size to 92. The goodness of fit statistics for this structural equation model were as follows: The RMSEA was 0.000 [0.000, 0.003], p = 0.999, CFI = 1.000, and TLI = 1.001. These fit statistics indicate a strong fit for the model, better than the initial model. Modification indices were not considered for this model due to the theoretical underpinnings of the model specification, the analysis of the correlation tables and confirmatory factor analyses, and the information gained from the initial model prior to the final specification of this model. Results in table 45 reveal that the model supports the theoretical relationship between principal behaviors, principal style, district supports, and the measured outcome of teacher behaviors. These results provide support for the existence of both the constructs embedded within the latent variables, as well as the impact of principal behaviors, principle style and district support can have on the behavior of teachers. In the discussion to follow, I will consider the factor loadings first for each factor, and then discuss the regression further.

Table 45
Data-Driven Decision-Making Teacher Behavior Model *(n = 92)*

	Estimate	Std. Err	Z-value	P(>|z|)	Std. Est.
Latent Variables					
prinbehavior <-					
t20behavior_past	0.822	0.037	22.159	0.000***	0.822
t20behavior_time	0.801	0.040	20.147	0.000***	0.801
t20behavior_lead	0.946	0.015	62.877	0.000***	0.946
t20behavior_demonstrate	0.951	0.014	67.637	0.000***	0.951
t20behavior_feedback	0.867	0.028	31.119	0.000***	0.867
t20behavior_dialogue	0.912	0.021	44.419	0.000***	0.912
t20behavior_connect	0.879	0.028	31.540	0.000***	0.879
prinstyle <-					
t19style_vision	0.822	0.039	21.101	0.000***	0.822
t19style_goals	0.777	0.044	17.733	0.000***	0.777
t19style_inst	0.724	0.062	11.758	0.000***	0.724
t19style_pdplans	0.879	0.036	24.584	0.000***	0.879
t19style_finance	0.749	0.055	13.652	0.000***	0.749
t19style_account	0.878	0.038	23.074	0.000***	0.878
distsupport <-					
t22distsupport_expertise	0.927	0.026	35.010	0.000***	0.927
t22distsupport_expectations	0.876	0.027	32.635	0.000***	0.876
t22distsupport_tools	0.709	0.061	11.667	0.000***	0.709
t22distsupport_pd	0.896	0.028	32.153	0.000***	0.896
t22distsupport_collect	0.837	0.044	18.978	0.000***	0.837
teachfreq<-					
t17freq_indgoals	0.651	0.075	8.681	0.000***	0.772
t17freq_classgoals	0.650	0.071	9.104	0.000***	0.771
t17freq_aggregate	0.650	0.070	9.308	0.000***	0.771
t17freq_whole	0.712	0.081	8.760	0.000***	0.845
t17freq_smallgroup	0.532	0.092	5.758	0.000***	0.631
t17freq_indstud	0.566	0.084	6.716	0.000***	0.672
t17freq_inter	0.207	0.065	3.164	0.002**	0.246
Regressions					
teachfreq <-					

prinbehavior	0.819	0.370	2.216	0.027*	0.691
prinstyle	-0.573	0.371	-1.542	0.123	-0.483
distsupport	0.300	0.147	2.049	0.040*	0.253
Covariances					
prinbehavior, prinstyle	0.788	0.052	15.124	0.000***	0.788
prinbehavior, distsupport	0.437	0.084	5.218	0.000***	0.437
prinstyle, distsupport	0.461	0.087	5.315	0.000***	0.461

Note: * = 0.05, ** = 0.01, *** = 0.001

The measurement model as represented by three constructs representing conditions influencing teacher data-driven decision-making, principal behavior, principal leadership style, and district support all had relatively uniform factor loadings of their underlying survey questions. These ranged from 0.801 to 0.951 for principal behaviors, 0.777 to 0.879 for principal style, and 0.709 to 0.927 for district supports. These narrow ranges are positive, in so far as all of the survey questions successfully captured the underlying factors. However, the drawback of these narrow factor loadings is that they don't provide a way to differentiate between the relative effectiveness of the individual behaviors or supports in influencing teacher behaviors.

As for the structural model, principal behaviors in support of data-driven decision making are strongly associated with a positive increase in teacher data-driven decision-making, with a standardized coefficient of 0.691. This relationship is consistent with the initial model. The next most influential coefficient is that of principal style, which continues to have an inverse relationship when considering degree of distributed leadership style as regressed against teacher behaviors in data-driven decision-making (b = -0.483). This negative association can't be completely dismissed when considering the disagreement in the literature as to whether a distributed or prescriptive model of leadership was most effective in increasing data-driven decision-making by teachers. However, the interpretation of this relationship in the model must consider the lack of statistical significance for this portion of the model. Finally, district support has a moderate but positive effect on improving teacher data-driven decision-making (b = 0.253).

This is different from the initial model and could be a result of the removal of relevance and training factors from the model. This lesser relative impact is also logical considering that the district office is an organizational level removed from a school site, resulting in less of an impact on teacher practice. Finally, the (mostly) single district design of the study could be reflected in the results through lower observed variation. With more districts in the study, this relationship might look different.

Linear Mixed Model

The initial structural model provided evidence for principal leadership, principal leadership style, and district support as influencing teacher data-driven decision-making behaviors. However, the model has one shortcoming: the lack of attention to the hierarchical contexts for the teachers in the study. To ensure that the findings still held when site level variation were accounted for, I constructed a linear mixed model taking into account the school for each teacher responding to the survey. Using the structural model created in the previous section, I created factor scores for each respondent without missing responses, and used those factor scores as inputs into the linear mixed model. This mixed model was analyzed utilizing Rstanarm, a complimentary program to the RStan package, used for general Bayesian statistical computing.

A linear mixed model was fit with Markov Chain Monte Carlo, with teacher behaviors as the outcome variable, principal leadership behaviors, principal leadership style, and district support as the predictors, and the intercept was allowed to vary by school. Due to the normalized factor scores, the model was specified with weakly informative normal priors also with a mean of 0 and a sd of 1. The results of the mixed model from are reported below in table 46, with the mean of the parameter estimate, the standard deviation of the posterior distribution, as well as the

50% credible intervals as well as 95% credible intervals. These same results are plotted in the figure below.

Table 46
Summary of Results of MCMC Linear Mixed Model

	mean	sd	2.50%	25%	50%	75%	97.50%
(Intercept)	-0.04	0.11	-0.25	-0.11	-0.04	0.03	0.17
prinbehavior	0.82	0.17	0.48	0.70	0.82	0.93	1.15
prinstyle	-0.61	0.19	-0.97	-0.74	-0.61	-0.48	-0.24
distsupport	0.35	0.11	0.13	0.27	0.35	0.43	0.58
(Intercept - School A)	-0.14	0.19	-0.62	-0.24	-0.09	0.00	0.13
(Intercept - School B)	0.02	0.15	-0.29	-0.05	0.01	0.09	0.36
(Intercept - School C)	0.02	0.15	-0.30	-0.05	0.01	0.09	0.37
(Intercept - School D)	0.09	0.17	-0.19	-0.01	0.04	0.17	0.52
(Intercept - School E)	-0.02	0.15	-0.36	-0.09	-0.01	0.05	0.30
(Intercept - School F)	0.04	0.15	-0.24	-0.03	0.02	0.11	0.39
(Intercept - School G)	-0.06	0.16	-0.44	-0.13	-0.03	0.02	0.21
(Intercept - School H)	0.12	0.19	-0.15	0.00	0.06	0.20	0.62
(Intercept - School I)	0.03	0.16	-0.28	-0.04	0.01	0.11	0.41
(Intercept - School J)	0.00	0.16	-0.35	-0.06	0.00	0.07	0.34
(Intercept - School K)	-0.12	0.22	-0.69	-0.21	-0.05	0.01	0.18

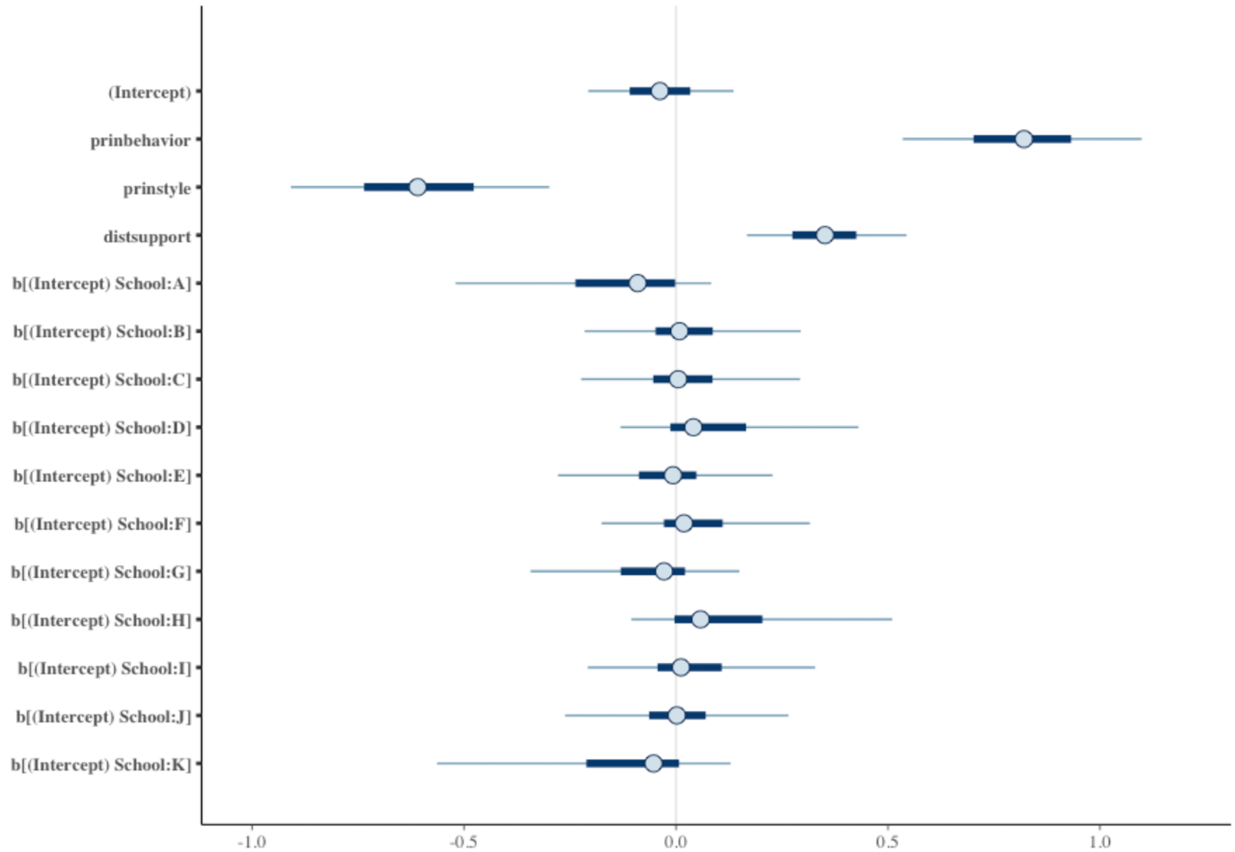

Figure 28. Plot of Credible Intervals for Linear Mixed Model Outputs

The model results in similar outcomes as the structural model, with the estimated beta coefficients for the three main factors remaining very similar: principal behavior (b = 0.82) is within a rounding adjustment of the structural model (b = 0.819). Principal style continues to have a negative association (b = - 0.61), with a slightly higher magnitude than in the structural model (b = -0.573). Finally, district support has the smallest coefficient (b = 0.35), once again slightly higher than in the structural model (b = 0.030) Interestingly, the credible intervals for both of these principal level measures is higher than the district measure, probably as a result of variation between principals that wasn't captured with the varying intercepts.

There is some variation in intercepts across schools. The estimated intercept (posterior mean) for school A was -0.14, as compared with school H with an estimate of 0.12. However, the 50% credible intervals for both of these schools include 0, meaning that there is a 50% chance that the results are no different than a 0 variation from the mean. It seems likely that additional teacher responses from a given site would help to narrow the credible intervals, helping to convincingly differentiate a site as having low or high data-driven decision-making.

Summary of Findings

There are several key findings from this study that provide the basis for the discussion in the final chapter of this dissertation. They are as follows:

Research Question 1a

Among various kinds of data available to teachers and principals in making data-driven decisions, what is the ***relative level of availability of that data?***

- Teachers generally report most types of student data as being easy to access (Table 7), including state achievement data, English Learner data, district assessment data, site benchmarks, and attendance data. One exception is suspension data is considered more difficult to gain access to. Parent and teacher survey data also ranks lower in perceived difficulty of access. Principals tended to rate the ease of access to data higher than their teachers.

Research Question 1b

Among various kinds of data available to teachers and principals in making data-driven decisions, what is the **relative frequency of use of that data**?

- Teachers use a variety of data types to perform their duties. The frequency of use is positive associated with the availability of data (Table 8). Survey data is rarely used, while suspension and attendance data are considered slightly more often (Table 6). The closer the data gets to being generated at the site, the more often it is used, with site and teacher created assessments being used weekly or more by a majority of teachers.

Principals tended to overestimate the amount of use of suspension data as compared to their teachers, but were relatively more accurate in predicting the reported frequency of use of academic data by their teachers (Table 25/Figure 12).

Research Question 2a

When considering conditions potentially influencing use of evidence at schools, including district office supports, principal leadership behaviors, principal leadership styles, prior training, and attitudes towards data use, to what extent ***do teachers experience these conditions****?*

- On average, teachers report district office supports occurring only some of the time, scoring their districts an average of 2.94-3.40 on a five point scale, with the collection of district and state assessment information for sites scoring the highest (Table 19).
- Teachers report that principal leadership behaviors occur a little more often than district supports, with a range of 3.19 to 3.84 on a five point scale (Table 18). Principals most often designate time during collaboration for data-analysis or decision-making.
- There is a strong tendency for sites to report highly distributed leadership styles by their principals, with results between 3.49 and 4.38 on a five point scale (Table 16). Principals most often are developing and implementing a joint vision with their staffs.
- Effective training for data-driven decision-making seems to occur most often in a job-embedded context (Table 15). When asked, teachers reported low amounts of effective training for training for data-driven decision-making in their undergraduate (m = 2.33) and credential program (m = 2.86). Instead, site level staff development (m = 3.01), district sponsored staff development (m = 3.07), and team level collaboration (m = 3.22) had higher reported amounts of effective training. Professional conferences did not do well either (m = 2.76).

- Attitudes towards data relevance were mixed, with teachers reporting data to be moderately relevant for most activities, including curriculum and instruction (Table 13), intervention (Table 14), and setting school goals (Table 11). Teachers found data to be much less relevant when considering teacher evaluation (Table 12). Generally, achievement data (State testing, English Language Acquisition, curriculum embedded assessment, and site/teacher created benchmarks) were viewed as more relevant in all of these areas of use as compared to non-academic data, such as suspension, attendance, or parent or teacher survey data.

Research Question 2b

When considering conditions potentially influencing use of evidence at schools, including district office supports, principal leadership behaviors, principal leadership styles, prior training, and attitudes towards data use, to what extent ***do principals experience these conditions****?*

- When conditions and supports were considered by principals, results were somewhat consistent with teachers.
    - On average, principals tended to report higher levels of district support than teachers, but usually within one standard deviation of the teacher average perception (Table 37, Figure 24).
    - Teachers and principals were most aligned when considering the role of data in performing teacher evaluation; that is, they both were opposed to it (Table 31/Figure 18). The area of greatest contrast was that principals had a tendency to see data as more important in determining intervention than teachers (Table 30/Figure 17).

Research Question 3

To what extent do teachers engage in processes for interpreting evidence at schools?

- Teachers rated themselves fairly highly in data-driven decision-making across multiple activities (Table 23). Teachers identified themselves as targeting students for intervention the most, with a mean of 4.72 on a five-point scale. The lowest reported behavior was analyzing aggregate data with other teachers (m = 3.88).

Research Question 4

Is there a relationship between types of evidence used by teachers and conditions influencing use of evidence, and the extent to which teachers engage in processes for interpreting evidence at schools?

- There is a relationship between conditions influencing data-driven decision-making, including principal leadership behaviors, principal leadership style, and district supports, and teacher behaviors in using data based upon the structural equation models and hierarchical models. Principal leadership behaviors are most positively associated, distributed leadership style has a moderate negative effect, and district support has a weak, but positive effect on behavior. There was not evidence of a relationship of teacher behaviors with other survey factors, including frequency of use of data, perceptions of relevance, availability of data, expertise in using data, and principal and district expectations. Site level variation was minimal, when observed, and was not different than 0 within a 50% credible interval when analyzed through a Markov Chain Monte Carlo linear mixed model.
- When correlations are analyzed on the basis of individual conditions and teacher behaviors, those correlations revealed some relationships between individual conditions or supports for data-driven decision-making and specific teacher data-driven decision-

making behaviors (Table 43). The highest polychoric correlation observed was 0.41. Some of the key relationships scoring above r = 0.3 are as follows:

- Credential classes have a positive relationship to whole class teacher behaviors, such as setting class goals and tailoring instruction for the whole class.
- District staff development had a positive relationship to changing instructional strategies for individual students.
- District expectations are positively related to an increase in aggregate analysis of data.
- A higher distributed leadership style was notably associated with tailoring instruction for the whole class.
- All of the principal data-driven leadership behaviors studied were positively associated with class level teacher behaviors, such as setting class goals, tailoring instruction for the class, and aggregate analysis with other teachers. Of those, the most highly associated principal behaviors with those teacher behaviors were engaging in dialogue regarding data-driven decision-making, demonstrating the process of DDDM, and providing feedback on teacher data practices
- District supports, such as providing expertise for sites in implementing DDDM, as well as setting expectations for data-driven decision-making, were positively associated with increased teacher behaviors in setting class goals, aggregate analysis, and tailoring instruction for the whole class.

CHAPTER 5: CONCLUSION

Introduction

In this chapter, I will discuss some implications of the findings of this study for both district leaders and principals if they would like to encourage data-driven decision-making. These implications for practice are especially salient as districts undertake the work of continuous improvement as encourages by the accountability system, as well as other frameworks for improvement such as that provided by improvement science. Data plays a central role in both the accountability system, as wells in internal reform efforts. In addition, I'll discuss some key limitations of the study as performed. Finally, I'll close with some recommendations for future research on the effect of district and site leadership on teacher data-driven decision-making behaviors.

Implications of the Research

This research examined numerous facets of data-driven decision-making at the school and district level that ultimately promote teacher behaviors in using data. While the recommendations below are wide ranging, it is essential that I emphasize that the core of the findings of this study center around the role of leadership, both at the district and site level. The final results of this research indicated that principal leadership behaviors are the most positively associated with teacher behaviors among all of the survey items. These behaviors require principals to take proactive steps to build the capacity of teachers to make meaning out of their data. Site leaders shouldn't apply each behavior in isolation as part of yet another checklist, but instead use it as an opportunity to reflect on teacher practice, diagnose needs, and meet them through the identified strategies.

Recommendation One*: District leaders should improve access to and build capacity in the utilization of suspension and attendance data by teachers and should increase awareness among principals about that need.*

Marsh et al. (2006) and Datnow and Park (2014) alluded to the increasing use of non-achievement outcomes in data-driven decision-making. However, one key contextual factor for California schools as of the writing of this dissertation is that the State of California is going through the rollout of a key data element of a new state accountability system, known as the California School Dashboard (Tira, 2017). Performance on this accountability system is based upon multiple measures, including academic performance, English learner progress, as well as suspension rate and chronic absenteeism. This is a departure from the previous accountability system in which only academic results were considered as part of the academic performance index. Not meeting expectations on attendance or suspension measures has the same implications for a site or district as not meeting academic expectations. Schools and districts can initially expect to receive a public identification for technical assistance, which eventually could evolve into intensive support, a status which has yet to be clearly identified by the California Department of Education.

It is in this new accountability context that some of the basic findings of this study can be effectively applied. Most simply, we know that suspension and attendance data are not frequently used by teachers, and teachers also state that it is especially difficult to get access to suspension data. Teachers also feel particularly unprepared to use suspension data in the context of data-driven decision-making. Compounding this gap is that principals have a tendency to report higher frequency of use of and higher levels of access to suspension data than teachers. Therefore, districts should work towards improving access to and capacity in using data that under the old system was not relevant to teacher's day to day work, such as attendance and suspension data. The inclusion of this data in the accountability system is a reflection of the perception among policy-makers that behavior and attendance are closely tied to academic outcomes.

This idea of improving access to suspension and attendance data, and providing training, is especially relevant when considering the study's findings in regards to the weak but positive association to district supports in influencing teaching behavior. The district behaviors most supported by the research in influencing teacher behaviors are as follows:

- Building capacity
  - Providing expertise on data use through central office personnel. This expertise is especially effective in promoting group level data use by teachers, such as for adjusting whole class instruction, and setting class goals.
- Improving access
  - Providing supplementary technological or other tools for facilitating data use
  - Collecting district and state assessment information and provide it in a timely fashion for sites

Recommendation Two: *District leaders should continue to provide training on data-driven decision-making in a variety of settings, including district staff development, site level staff development as well as during team level collaboration. They should also continue to set high expectations for data use by the teaching staff.*

Honig's (2008) Organizational Learning Theory approach to understanding the role of the central office places the district office squarely at the center of supporting teaching and learning, as opposed to the traditional managerial and administrative role it has historically had. While the structural model found that training was not statistically significantly associated at the alpha = 0.05 level with an increase in teacher behaviors in data-driven decision-making, there was a small positive association between training and DDDM that can be taken advantage of as part of a larger system of promoting DDDM. In addition, teachers reported that they were not as highly prepared to undertake DDDM due to the lowest level of effective training in their undergraduate degree programs and credential programs and in professional conferences. The district and site staff development setting and team level collaboration setting were considered to be more frequently effective by teachers in their survey responses. District training is especially needed when seeking to improve teacher practice in adjusting instruction on an individual student basis. Once again, district behaviors in supporting data-driven decision-making, especially that of providing central office expertise, are salient towards accomplishing the goals of this recommendation.

Recommendation Three: *Principals should seek to increase data-driven decision-making by teachers by engaging in the leadership behaviors identified in the literature and supported by the study.*

Principal behaviors as identified by Marsh and Farrell (2015) had the highest effect on teacher data-driven decision-making behaviors as compared to all other conditions supports data-driven decision-making. The study supports the following behaviors as having the strongest positive relationship:

- Demonstrating the process of making instructional decisions in response to data
- Engaging in dialogue with teachers regarding the process of data analysis or instructional decision making
- Observing and providing direct feedback of teacher practices in analyzing and using data

These principal behaviors also had a weak positive relationship to teacher behaviors:

- Asking questions about past experience with using student data to inform decision-making
- Designating time during collaboration or shared planning for data analysis or decision-making
- Leading analyses of school or classroom data with site staff

As a reminder, this work is continuous, and should not be thought of as isolated steps in promoting teacher data use; instead, principals should be regularly considering the needs of their staff, and employing appropriate strategies as their conversations and interactions with teachers reveal those needs.

Recommendation Four: *District and site leaders should find ways to improve perceptions of the relevance of data that is not locally generated.*

Teachers reported increased relevance of site-based measures across multiple uses of the data. Site and teacher created assessments are used weekly or more by a majority of teachers, while district and state data was used less frequently. Given the time between cycles of state assessment, it is perhaps not surprising that state data is used only infrequently. On the other hand, attendance data is generated on daily basis was not found to be used regularly. In addition, survey data of parents or teachers is being used as part of the local as districts determine whether they met the state priorities of parent engagement, or of implementation of state standards.

At its core, this recommendation is about the challenge of taking external accountability measures, which have a rather poor record of transforming the overall education system, and creating a system of internal accountability. This perception of low relevance could be a reflection of a lack of an internal accountability system as it relates to these measures. It would appear that the internal accountability exists for those site and local benchmarks. The key is taking that level of ownership and trust in the data as implied by the findings of the study (though not directly measured) and spreading it among a wider range of important data.

Limitations of the Study

This study had some key limitations which affect the interpretation and ultimate use of the results. These limitations include concerns raised by the research design, as well as limitations that cropped up once results from the survey were analyzed.

Research Site and Sample Size

The survey took place primarily in a single school district in California, with only one school recruited from another district. While there were a range of demographics that these schools represented, the underlying relationships between all of the survey variables possibly reflective only of a specific district context, and not generalizable beyond that district. This issue is somewhat mitigated through the number of schools recruited, as eleven schools were included, enough to be able to parse out school hierarchical effects to some extent, improving the underlying regression coefficients. By employing a sampling plan of schools that results in a variety of demographic contexts, combined with the loosely coupled nature of schools in relation to their district office, some level of generalizability will still be possible for the research. However, the smaller sample size was partially responsible for preventing the credible intervals from being outside of 0 when considering varying intercepts.

In addition, a larger overall teacher sample size could help on a few levels: first, it would enable more complex models with additional parameters to estimate to successfully converge. Paths between individual items were for the most part precluded due to the rapidly increasing number of parameters to estimate in such a model. On a related, the larger sample would also enable the analysis to take place in a single stage, instead of the sequential process of creating a structural model, then a hierarchical model. Once again, the sequential process decreased the number of parameters to be estimated at a given time.

Finally, the decision to limit the sample to elementary schools limits the generalizability of the research outside of the elementary setting. There are many different organizational factors at the secondary level, as compared to the elementary level, such as the larger campus population, the organization of teachers into subject area departments, the larger number of student contacts experienced by those teachers, as well as the differing way that leadership might be expressed that occurs as more site administrators are added to a campus.

Disconnect between results on different questions

The survey had some questions that described some of the conditions that could influence teacher DDDM in two parts of the survey. Unfortunately, some of these dual measures resulted in possibly conflicting descriptive results. One example was in the teacher behaviors, in which more teachers reported that they used student data to identify students to target for intervention than any of the other teacher behaviors of interest in the survey. However, when asked regarding the relevance of differing types of data to differing types of activities, teachers tended to rate most data use for intervention as less relevant as compared to data use for curriculum and instruction or school goal setting. While it is possible that other types of data are being used than listed for identifying students for intervention, the disconnect is at least worth noting.

Similarly, teachers rated themselves noticeably lower at analyzing data with other teachers jointly during collaboration time than the other survey measures of their behaviors. However, across all of the leadership behaviors measured in the survey for principals, they rated principals most highly in designating time during collaboration for shared planning for data analysis. This apparent contradiction could represent an issue with the underlying survey and its questions. However, one possible way to reconcile these differences between teacher and principal behaviors is to conclude that principals are highly effective in providing teachers time for collaborative data analysis, but teachers are not effectively using that time provided.

Additionally, the correlation analysis showed that district expectations when considered on their own were not strongly associated with an increase in teacher behaviors in DDDM. However, district expectations were one of the supports identified as part of the larger district support factor utilized in the structural model. When included in the district supports factor, expectations were a statistically significant contributor to the factor, a factor which then had a statistically significant impact on teacher behaviors. The one difference in how expectations where measured between the district supports and the standalone question was that an answer of "I don't know" was not specified for the district supports, but it was scored as a three on a five-point Likert scale for the standalone question regarding district expectations.

Suspension Data Type

Some of the findings and recommendations regarding the use of data were in regards to suspension data. The incidence of suspension is lower at the elementary level, perhaps explaining some of the findings in regards to suspension being less accessible and less frequently used. That being said, a possible solution would be to ask teachers to respond to questions regarding "behavior" data, instead of "suspensions". Behavior data is a broader term encompassing many minor negative behaviors that do not result in suspension, as well as also possibly including data regarding positive behaviors by students, and the accompanying rewards or incentives for such behavior. Teachers might be more find behavior data to be more available and have higher self-reported expertise in its use.

Scales for Measures

The descriptive results for the survey revealed some issues with the survey scales that might impact the interpretation of the model results. As one example, the principal leadership style questions were written in such a manner that survey respondents may have perceived the behaviors as having a positive association, thereby increasing the leadership style score. Principals certainly self-reported high levels of distributed leadership styles, with principals selecting almost all fours and fives on this scale. The scale could have been improved with prescriptive leadership style descriptors cross scaled with distributed leadership descriptors, so that the bias towards rating the principal highly wouldn't have as much of a possible effect on this particular outcome.

This tendency towards higher scores was especially apparent on the outcome survey questions, as teachers self-reported their behaviors to be very high in performing data-driven decision-making as measured through the six survey questions. This decrease in variation of the outcome measure has some implications for the ability of the survey instrument to discriminate between lower and higher levels of DDDM by teachers, and accordingly the final models are probably less able to measure the effects of the other conditions in relation to teacher DDDM. The scale of 1=Never to 5=All the time probably needs to be replaced with another scale more likely to produce a range of responses by teachers taking the survey that are not all uniformly positive.

One final consideration in regards to the availability metric used in the study: the survey questions did not differentiate between different reasons why certain kinds of data might be difficult to access. First, there is data that doesn't exist. A good example of this was the K-2 teachers reporting almost no use of state assessment data, because it doesn't exist. Second, there is data that does exist, but is not easily available for the teacher to access. These differing types of availability have much different implications for practice, and so should be further delineated in future iterations of the survey instrument.

Recommendations for Future Research

These limitations also provide some ideas for how future research could build upon the foundation set by this study. One set of recommendations centers on continuing the study in its current form, but with some modifications to improve its generalizability. In alignment with the limitation regarding sample size, one easy way to improve generalizability would be to **increase the sample size**, while also getting a **greater variety of districts and schools** to participate in the study. Access and time considerations made the inclusion of the single main district a sufficient first step, but if the survey is to gain greater external validity, the sample must reflect a greater representation of the population of all teachers and principals. The model specified in this research should be tested against these additional districts to provide cross-validation of the model as developed over the course of this study. This increased sample size could also help with creating a more sophisticated model, perhaps incorporating individual district supports or principal behaviors and their effect on teacher behaviors. There are advantages into combining the individual behaviors into a latent factor, such as the number of parameters needing to be estimated decreases. Also, the resulting factor scores are easier to utilize in a regression against the outcome variable of teacher behaviors in DDDM. While the correlations presented in this work were a starting point for understanding those relationships, a model jointly incorporating the individual relationships might provide stronger support for some of the findings of this research.

In addition, an alternative way to specify the model of with this data would be to use frequency of use of the eight data types as the outcome variable of the survey, as opposed to the six identified teacher behaviors in using data. The frequency of use questions had a more normal distribution as compared to the skewing apparent in the teacher behavior items, which would have possibly enabled other more intricate relationships between individual questions to be explored in the analysis, rather than just using a composite factor score or average to represent groups of questions.

Another area of possible comparison and exploration in future research would be in regards to the level of knowledge of the Local Control Accountability Plan (LCAP), as well as the perceived effect of the LCAP on teacher practice. The LCAP is a key feature of the local orientation of the new system of continuous improvement, in which districts respond to data, identify actions to meet needs identified by that data, and evaluate the effectiveness of actions from the previous year. While I asked these questions on the survey instrument, the results generally indicated little knowledge of the LCAP, and either no perceived effect or a neutral perceived effect of the LCAP (Tables 21/22). Given additional time in the new accountability system, future research might provide additional insight on the effects of LCAP on teachers, including in data-driven decision-making.

There are a few ways in which future research on the LCAP could dive deeper. At the site level, sites are required to adopt the Single Plan for Student Achievement (SPSA), a document which is supposed to be closely aligned with the LCAP. A document analysis of the LCAP and the accompanying site SPSAs would possibly be a tool by which to measure impact on the site that otherwise would go unreported by teachers. This document analysis could then be used with survey questions regarding the SPSAs to capture an indirect effect of the LCAP on teacher practice, both in general, as well as specifically in regards to data-driven decision-making.

Another consideration in regards to future study would be to **increase the sample size within a given site**. The credible intervals generated by the Markov Chain Monte Carlo for the site intercepts were not small enough to differentiate higher and lower intercept scores as being different from zero. However, doubling or tripling the number of teachers would help to shrink that interval, allowing the identification of sites as high or low in teacher DDDM. Gaining access to teachers was exacerbated by the size of the survey instrument, with the average survey taking 17 minutes to complete. While survey incentives helped with the ultimate completion of the survey, the time and number of questions did cause a small number of teachers to never complete the survey once started. Careful culling of questions not likely to contribute towards understanding the leadership behaviors that most effective promote teacher DDDM could improve the completion rate of the survey.

Beyond just improving the implementation of this particular survey instrument, future research should continue to **clarify the role that principal style has in promoting DDDM behaviors**. While the survey tentatively identified a more prescriptive leadership style as positively associated with teacher DDDM behaviors, this finding is muddied by the high correlation between distributed leadership style and leadership behaviors, along with the positive correlations across individual questions regarding leadership style and teacher behaviors. With this being one of the areas of disagreement across multiple researchers, it continues to be an opportunity for future study. This could result in a particular style being determined to be more efficient. Or, more likely, researchers could identify other contextual factors that explain why prescriptive leadership is effective in certain circumstances, but not in others.

One final connection that needs to receive further study is loosely made in the existing literature: the relationship between increased data-driven decision-making behaviors by teachers, and improved student outcomes, whether academic or behavioral. The ultimate goal of data-driven decision-making is to improve student outcomes, so **future studies should determine if changes in teacher behaviors in DDDM actually have an impact on those outcomes**.

Appendix A - Teacher Survey

Data-Driven Decision-Making Survey - Teacher

Study Information Sheet

UNIVERSITY OF CALIFORNIA LOS ANGELES
STUDY INFORMATION SHEET

A Study of the Conditions Influencing Data-Driven Decision-Making by Teachers

Nicholas Chitwood, graduate student in Education from the University of California, Los Angeles, is conducting a research study focused on data-driven decision-making by teachers, and the school and district conditions influencing data-driven decision-making by teachers.

For purposes of this survey, data-driven decision-making generally refers to the use of student data such as state achievement results, suspension results, or opinion data for educational decision making in areas including but not limited to curriculum and pedagogy, as well as in the allocation of resources.

You were selected as a possible participant in your study because your school district agreed to participate in the study. Your participation in this study is voluntary.

Why is this study being done?
This study is being conducted in partial fulfillment of the requirements for the degree Doctor in Education. In addition, the goals of the study are to better understand the kind of evidence used by teachers in data-driven decision-making, the conditions influencing data-driven decision-making (DDDM), as well as the processes of data-driven decision-making by teachers.

What will happen if I take part in this research study?
If you volunteer to participate in this study, the researcher will ask you a single online survey of no more than 15 minutes. The survey instrument will include questions concerning your background as an educator, perceptions of DDDM as a process, as well as perceptions of principal and district-level supports for DDDM.

Are there any potential risks or discomforts that I can expect from this study?
There are no anticipated risks or discomforts.

Are there any potential benefits if I participate?
Your participation in this study will be used to provide your school district and site

leadership feedback regarding current implementation of data-driven decision-making by teachers in your district. This feedback could be used to improve training and supports for data-driven decision-making. Findings from this study in general could also be used to inform practitioners and researchers regarding current school, and district practices regarding DDDM that best promote use of data by teachers.

Will I be paid for participating?
The first twelve teachers from your school site completing and submitting the whole survey will receive a $5 Target gift card.

Will information about me and my participation be kept confidential?
Any information that is obtained in connection with this study and that can identify you will remain confidential. It will be disclosed only with your permission or as required by law. Confidentiality will be maintained by means of removing identifying information from datafiles and storing all datafiles in secure computer servers accessible only to approved study staff, or on an encrypted and password protected portable computer. This anonymized information may be retained beyond the time period of the study for use in future research as well.

What are my rights if I take part in this study?
You can choose whether or not you want to be in this study, and you may withdraw your consent and discontinue participation at any time. Whatever decision you make, there will be no penalty to you, and your decision not to participate will not be disclosed to your employer. You may refuse to answer any questions that you do not want to answer and still remain in the study.

Who can I contact if I have questions about this study?

The researcher, or the dissertation advisor:
If you have any questions, comments or concerns about the research, you can talk to the researcher or the dissertation advisor. Please contact the study principal investigator, Nick Chitwood, at 559-303-7730 or nickchitwood@ucla.edu, or Mark Hansen, PhD, from the Department of Education at 310-794-9149 or markhansen@ucla.edu

UCLA Office of the Human Research Protection Program (OHRPP):
If you have questions about your rights while taking part in this study, or you have concerns or suggestions and you want to talk to someone other than the researchers about the study, please call the OHRPP at (310) 825-7122 or write to:

UCLA Office of the Human Research Protection Program
11000 Kinross Avenue, Suite 211, Box 951694
Los Angeles, CA 90095-1694

1) Please select the appropriate consent statement below.*

( ) I understand the study described above and I agree to participate.

( ) I do not agree to participate.

Survey Questions

Part 1: Please provide this information about your background as an educator and the students you work with.

Shortname / Alias: t02district

2) District Name

____

Shortname / Alias: t03school

3) School Name

____

Shortname / Alias: t04role

4) What role do you have at your site?

( ) Classroom Teacher (General ed)

( ) Classroom Teacher (RSP)

( ) Classroom Teacher (SDC-Mild/Mod)

( ) Classroom Teacher (SDC-Mod/Severe)

( ) Instructional Coach

( ) Intervention/Literacy Teacher

Shortname / Alias: t05grade

5) Grade Span
Which grade(s) do you teach (Please check all that apply)?

[ ] TK

[ ] K

[ ] 1

[ ] 2

[ ] 3

[ ] 4

[ ] 5

[ ] 6

Shortname / Alias: t06yearsprincipal

6) Years, at the end of this school year, that you have worked with the current principal:

____

Shortname / Alias: t07yearsteacher

7) Years experience as a teacher at the end of this school year:

____

Shortname / Alias: t08majocat

8) What categories would your undergraduate major belong to from the following list?

[ ] Education (Liberal Arts)

[ ] Arts and Humanities

[ ] Biological Sciences

[ ] Business

[ ] Engineering

[ ] Physical Sciences

[ ] Other Professional (Architecture, pre-med, etc)

[ ] Social Sciences

[ ] Other - Write In

Shortname / Alias: t09perc_el

9) What percent of your students would be classified as English Learners?

0 _________________________[__]______________________________ 100

Shortname / Alias: t10perc_sped

10) What percent of your students are receiving special education services (RSP/SDC Push In, etc)?

0 _________________________[__]______________________________ 100

Background in and Perception of Data-Driven Decision-Making

> **A reminder: For purposes of this survey, data-driven decision-making generally refers to the use of student data such as state achievement results, suspension results, or opinion data for educational decision making in areas including but not limited to curriculum and pedagogy, as well as in the allocation of resources.**

Shortname / Alias: t11often

11) Teacher Forms of Data Used

How often do you analyze or make decisions using the following types of data?

	Never	About	Monthly	Weekly	Daily

		once a year			
State achievement data (CAASPP, CAA, SBAC, etc)	( )	( )	( )	( )	( )
English language acquisition data (CELDT, ELPAC)	( )	( )	( )	( )	( )
District created/curriculum embedded assessments	( )	( )	( )	( )	( )
Site/teacher created benchmarks	( )	( )	( )	( )	( )
Suspension data	( )	( )	( )	( )	( )
Attendance data	( )	( )	( )	( )	( )
Parent survey data	( )	( )	( )	( )	( )
Teacher survey data	( )	( )	( )	( )	( )

Shortname / Alias: t12diff

12) Teacher Forms of Data Used

How difficult is it for you to gain access to the following types of data for purposes of decision making?

	1 Very difficult	2	3	4	5 Very easy
State achievement data (CAASPP, CAA, SBAC, etc)	( )	( )	( )	( )	( )

English language acquisition data (CELDT, ELPAC)	( )	( )	( )	( )	( )
District created/curriculum embedded assessments	( )	( )	( )	( )	( )
Site/teacher created benchmarks	( )	( )	( )	( )	( )
Suspension data	( )	( )	( )	( )	( )
Attendance data	( )	( )	( )	( )	( )
Parent survey data	( )	( )	( )	( )	( )
Teacher survey data	( )	( )	( )	( )	( )

Shortname / Alias: t13expert

13) Teacher Forms of Data Used

How would you rate your expertise in the interpretation of the following types of data for purposes of decision making?

	Basic	**Intermediate**	**Proficient**	**Advanced**
State achievement data (CAASPP, CAA, SBAC, etc)	( )	( )	( )	( )
English language acquisition data (CELDT, ELPAC)	( )	( )	( )	( )
District created/curriculum embedded assessments	( )	( )	( )	( )
Site/teacher created benchmarks	( )	( )	( )	( )

Suspension data	( )	( )	( )	( )
Attendance data	( )	( )	( )	( )
Parent survey data	( )	( )	( )	( )
Teacher survey data	( )	( )	( )	( )

Shortname / Alias: t14otherdata

14) Are there any other forms of data that you use that have not been identified in the questions above? If so, which kinds, and how often do you use it (Daily, weekly, monthly, yearly)?

____
____
____
____

15) Relevance of data to differing types of data-driven decision-making

How relevant are the following kinds of data in making decisions in the following areas?

	Setting goals and actions for school wide planning	Determinin g teacher effectivene ss/evaluati on	Adjusting core curriculum and instruction for students	Identifying students for academic or behavioral interventio n
State achievement data (CAASPP, CAA, SBAC, etc)				
English language acquisition data (CELDT, ELPAC)				

District created/curriculum embedded assessments				
Site/teacher created benchmarks				
Suspension data				
Attendance data				
Parent survey data				
Teacher survey data				

Shortname / Alias: t16train

16) Training and preparation in data-driven decision-making

To what extent have you received effective training or support in data-driven decision-making in the following settings?

	None at all	**Only a little**	**Some**	**A lot**
Undergraduate degree program	( )	( )	( )	( )
Teacher preparation program (credential program)	( )	( )	( )	( )
School district sponsored staff development	( )	( )	( )	( )
Professional conferences	( )	( )	( )	( )
Site level staff development	( )	( )	( )	( )
Team level collaboration	( )	( )	( )	( )

Teacher Behaviors

Part IV: This questionnaire is designed to provide a profile of teacher behaviors in data-driven decision-making. It consists of several behavioral statements that describe teacher data-driven decision-making practices and behaviors. You are asked to consider each question in terms of your self-perception of your behaviors over the past school year.

Read each statement carefully. Then click the option that best fits your job behavior or practice during the past school year. In some cases, these responses may seem awkward; use your judgment in selecting the most appropriate response to such questions. Try to answer every question. Thank you.

Shortname / Alias: t17freq

17) Teacher Behaviors in Data Use

How frequently do you use student data to...?

	1 Never	**2**	**3**	**4**	**5 All the time**
Set individual student improvement goals and targets	( )	( )	( )	( )	( )
Set class improvement goals and targets	( )	( )	( )	( )	( )
Analyze aggregate data with other teachers to inform joint action in meeting student needs	( )	( )	( )	( )	( )
Tailor instruction for the whole class	( )	( )	( )	( )	( )

Divide students into small groups to provide interventions	( )	( )	( )	( )	( )
Change instructional strategies for individual students	( )	( )	( )	( )	( )
Identify students to target for intervention	( )	( )	( )	( )	( )

Principal Behaviors

Part III: This questionnaire is designed to provide a profile of principal leadership in data-driven decision-making. It consists of several behavioral statements that describe principal leadership practices and behaviors. You are asked to consider each question in terms of your observations of the principal's leadership over the past school year.

Read each statement carefully. Then click the option that best fits the specific job behavior or practice of this principal during the past school year. In some cases, these responses may seem awkward; use your judgment in selecting the most appropriate response to such questions. Try to answer every question. Thank you.

Shortname / Alias: t18prinex

18) Expectations Regarding Data-Driven Decision-Making

Please indicate your agreement with the following statement:
My principal expects teachers in the school to use data to make decisions about instruction.

( ) Strongly disagree

( ) Disagree

( ) I don't know my principal's expectations in regards to data use

( ) Agree

( ) Strongly Agree

Shortname / Alias: t19style

19) Principal Leadership Style

How often does your principal . . . ?

	1 Never	**2**	**3**	**4**	**5 All The Time**
Develop and implement a joint vision with the staff regarding and purposes and aspirations of the school	( )	( )	( )	( )	( )
Set and monitor sitewide goals for student outcomes with staff	( )	( )	( )	( )	( )
Empower staff in instructional decision making in regards to curriculum and pedagogical strategies	( )	( )	( )	( )	( )
Evaluate and implement professional development plans with site staff	( )	( )	( )	( )	( )
Make decisions with site staff regarding the allocation of financial resources	( )	( )	( )	( )	( )
Encourage a commitment to shared accountability for student outcomes from all staff	( )	( )	( )	( )	( )

Shortname / Alias: t20behavior

20) Principal Data-Driven Leadership Behaviors

How often does your principal . . . ?

	1 Never	2	3	4	5 All the time
Ask questions about your past experience with using student data to inform decision-making	( )	( )	( )	( )	( )
Designate time during collaboration or shared planning for data analysis or decision-making	( )	( )	( )	( )	( )
Lead analyses of school or classroom data with site staff	( )	( )	( )	( )	( )
Demonstrate the process of making instructional decisions in response to data	( )	( )	( )	( )	( )
Observe and provide direct feedback of your practices in analyzing and using data	( )	( )	( )	( )	( )
Engage in dialogue with you regarding your process of data analysis or instructional decision making	( )	( )	( )	( )	( )
Encourage connections with other individuals with expertise (data analysis or pedagogical) that improves your ability to utilize data	( )	( )	( )	( )	( )

District Office Behaviors

Part IV: This questionnaire is designed to provide a profile of district leadership in data-driven decision-making. It consists of several behavioral statements that describe district leadership practices and behaviors. You are asked to consider each question in terms of your observations of the district's leadership over the past

school year.

Read each statement carefully. Then click the option that best fits the specific job behavior or practice of your district leadership during the past school year. In some cases, these responses may seem awkward; use your judgment in selecting the most appropriate response to such questions. Try to answer every question. Thank you.

Shortname / Alias: t21distexpect

21) Expectations Regarding Data-Driven Decision-Making

Please indicate your agreement with the following statement:
School district leadership expects teachers in the school to use data to make decisions about instruction.

( ) Strongly disagree

( ) Disagree

( ) I don't know what district leadership expects in regards to data use

( ) Agree

( ) Strongly agree

Shortname / Alias: t22distsupp

22) District Leadership Support Behaviors
How often does district leadership...

	1 Never	2	3	4	5 All the time
Provide expertise on data use through central office personnel	( )	( )	( )	( )	( )
Set expectations for data use in school improvement	( )	( )	( )	( )	( )
Provide supplementary	( )	( )	( )	( )	( )

technological or other tools for facilitating data use					
Develop expertise through professional development to meaningfully incorporate data use into decision making	( )	( )	( )	( )	( )
Collect district and state assessment information and provide it in a timely fashion for sites	( )	( )	( )	( )	( )

Shortname / Alias: t23lcapknow

23)

Local Control Accountability Plan

The new system of school funding known as the Local Control Funding Formula has created a new system of planning and accountability in California. One key part of this system is the Local Control Accountability Plan, which is adopted by the school district on an annual basis. How much knowledge do you have regarding the following elements of the Local Control Accountability Plan?

	None at all	Only a little	Some	A lot
LCAP Goals for the School District	( )	( )	( )	( )
LCAP Actions and Services for All Students	( )	( )	( )	( )
LCAP Actions and Services for Low Income Students	( )	( )	( )	( )
LCAP Actions and Services	( )	( )	( )	( )

for English Learners				
LCAP Actions and Services for Foster Youth	( )	( )	( )	( )
LCAP Metrics/Annual Measurable Outcomes	( )	( )	( )	( )

Shortname / Alias: t24lcapeffect

24)

<u>What effect</u> has the Local Control Accountability Plan had on your practice as a teacher in the following areas in the last year? If you don't have an opinion, please select "not applicable".

	Completely negative 1	Very negative 2	Somewhat Negative 3	Neither negative or positive	Somewhat Positive 5	Very positive 6	Completely positive 7	Not Applicable
Data-driven decision-making practices	( )	( )	( )	( )	( )	( )	( )	( )
Student curriculum	( )	( )	( )	( )	( )	( )	( )	( )
Intervention programs for at-risk students	( )	( )	( )	( )	( )	( )	( )	( )
Classroom Instructional strategies	( )	( )	( )	( )	( )	( )	( )	( )
School discipline/behavior systems	( )	( )	( )	( )	( )	( )	( )	( )

School Site Budgets	( )	( )	( )	( )	( )	( )	( )	( )
Personnel Decisions	( )	( )	( )	( )	( )	( )	( )	( )

Shortname / Alias: t25otherdist

25) District Leadership Behaviors

Are there any other ways in which district leadership either supports the use of Data-Driven Decision-Making which was not included above? Are there other things the district does that makes it difficult for you to engage in Data-Driven Decision-Making? Please use the space below to describe.

____

____

____

____

Thank You!

Thank you for participating in this study. Your response is very important to us.

Appendix B - Principal Survey

Data-Driven Decision-Making Survey - Principal

Study Information Sheet

UNIVERSITY OF CALIFORNIA LOS ANGELES
STUDY INFORMATION SHEET

A Study of the Conditions Influencing Data-Driven Decision-Making by Teachers

Nicholas Chitwood, graduate student in Education from the University of California, Los Angeles, is conducting a research study focused on data-driven decision-making by teachers, and the school and district conditions influencing data-driven decision-making by teachers.

For purposes of this survey, data-driven decision-making generally refers to the use of student data such as state achievement results, suspension results, or opinion data for educational decision making in areas including but not limited to curriculum and pedagogy, as well as in the allocation of resources.

You were selected as a possible participant in your study because your school district agreed to participate in the study. Your participation in this study is voluntary.

Why is this study being done?
This study is being conducted in partial fulfillment of the requirements for the degree Doctor in Education. In addition, the goals of the study are to better understand the kind of evidence used by teachers in data-driven decision-making, the conditions influencing data-driven decision-making (DDDM), as well as the processes of data-driven decision-making by teachers.

What will happen if I take part in this research study?
If you volunteer to participate in this study, the researcher will ask you a single online survey of no more than 15 minutes. The survey instrument will include questions concerning your background as an educator, perceptions of DDDM as a process, as well as perceptions of principal and district-level supports for DDDM.

Are there any potential risks or discomforts that I can expect from this study?
There are no anticipated risks or discomforts.

Are there any potential benefits if I participate?
Your participation in this study will be used to provide your school district and site

leadership feedback regarding current implementation of data-driven decision-making by teachers in your district. This feedback could be used to improve training and supports for data-driven decision-making. Findings from this study in general could also be used to inform practitioners and researchers regarding current school, and district practices regarding DDDM that best promote use of data by teachers.

Will I be paid for participating?
Those completing and submitting the whole survey will receive a $5 Amazon gift card.

Will information about me and my participation be kept confidential?
Any information that is obtained in connection with this study and that can identify you will remain confidential. It will be disclosed only with your permission or as required by law. Confidentiality will be maintained by means of removing identifying information from datafiles and storing all datafiles in secure computer servers accessible only to approved study staff, or on an encrypted and password protected portable computer. This anonymized information may be retained beyond the time period of the study for use in future research as well.

What are my rights if I take part in this study?
You can choose whether or not you want to be in this study, and you may withdraw your consent and discontinue participation at any time. Whatever decision you make, there will be no penalty to you, and your decision not to participate will not be disclosed to your employer. You may refuse to answer any questions that you do not want to answer and still remain in the study.

Who can I contact if I have questions about this study?

The researcher, or the dissertation advisor:
If you have any questions, comments or concerns about the research, you can talk to the researcher or the dissertation advisor. Please contact the study principal investigator, Nick Chitwood, at 559-303-7730 or nickchitwood@ucla.edu, or Mark Hansen, PhD, from the Department of Education at 310-794-9149 or markhansen@ucla.edu

UCLA Office of the Human Research Protection Program (OHRPP):
If you have questions about your rights while taking part in this study, or you have concerns or suggestions and you want to talk to someone other than the researchers about the study, please call the OHRPP at (310) 825-7122 or write to:

UCLA Office of the Human Research Protection Program
11000 Kinross Avenue, Suite 211, Box 951694
Los Angeles, CA 90095-1694

1) Please select the appropriate consent statement below.*

( ) I understand the study described above and I agree to participate.

( ) I do not agree to participate.

Survey Questions

Part 1: Please provide this information about your background as an educator and the students you work with.

2) School Name

____

3) District Name

____

4) Grade Span
Which grades are offered at your site?

[ ] TK

[ ] K

[ ] 1

[ ] 2

[ ] 3

[ ] 4

[ ] 5

[ ] 6

5) Years, at the end of this school year, that you have been a principal at your current site:

____

6) Years experience as a principal at the end of this school year:

____

7) What percent of your students would be classified as English Learners?

0 _________________________[__]______________________________ 100

8) What percent of your students are receiving special education services (RSP/SDC Push In, etc)?

0 _________________________[__]______________________________ 100

Background in and Perception of Data-Driven Decision-Making

A reminder: For purposes of this survey, data-driven decision-making generally refers to the use of student data such as state achievement results, suspension results, or opinion data for educational decision making in areas including but not limited to curriculum and pedagogy, as well as in the allocation of resources.

9) Teacher Forms of Data Used

How often do your teachers analyze or make decisions using the following types of data?

	Never	**About once a year**	**Monthly**	**Weekly**	**Daily**
State achievement data (CAASPP, CAA, SBAC, etc)	( )	( )	( )	( )	( )
English language acquisition data	( )	( )	( )	( )	( )

(CELDT, ELPAC)					
District created/curriculum embedded assessments	( )	( )	( )	( )	( )
Site/teacher created benchmarks	( )	( )	( )	( )	( )
Suspension data	( )	( )	( )	( )	( )
Attendance data	( )	( )	( )	( )	( )
Parent survey data	( )	( )	( )	( )	( )
Teacher survey data	( )	( )	( )	( )	( )

10) Teacher Forms of Data Used

How difficult is it for your teachers to gain access to the following types of data for purposes of decision making?

	1 Very difficult	**2**	**3**	**4**	**5 Very easy**
State achievement data (CAASPP, CAA, SBAC, etc)	( )	( )	( )	( )	( )
English language acquisition data (CELDT, ELPAC)	( )	( )	( )	( )	( )
District created/curriculum embedded assessments	( )	( )	( )	( )	( )
Site/teacher created benchmarks	( )	( )	( )	( )	( )
Suspension data	( )	( )	( )	( )	( )
Attendance data	( )	( )	( )	( )	( )

Parent survey data	( )	( )	( )	( )	( )
Teacher survey data	( )	( )	( )	( )	( )

11) Teacher Forms of Data Used

How would you rate your teachers' expertise in the interpretation of the following types of data for purposes of decision making?

	Basic	Intermediate	Proficient	Advanced
State achievement data (CAASPP, CAA, SBAC, etc)	( )	( )	( )	( )
English language acquisition data (CELDT, ELPAC)	( )	( )	( )	( )
District created/curriculum embedded assessments	( )	( )	( )	( )
Site/teacher created benchmarks	( )	( )	( )	( )
Suspension data	( )	( )	( )	( )
Attendance data	( )	( )	( )	( )
Parent survey data	( )	( )	( )	( )
Teacher survey data	( )	( )	( )	( )

12) Are there any other forms of data that your teachers use that have not been identified in the questions above? If so, which kinds, and how often do they use it (Daily, weekly, monthly, yearly)?

____

____

____

13) Relevance of data to differing types of data-driven decision-making

How relevant are the following kinds of data in making decisions in the following areas?

	Setting goals and actions for school wide planning	**Determining teacher effectiveness /evaluation**	**Adjusting core curriculum and instruction for students**	**Identifying students for academic or behavioral intervention**
State achievement data (CAASPP, CAA, SBAC, etc)				
English language acquisition data (CELDT, ELPAC)				
District created/curriculum embedded assessments				
Site/teacher created benchmarks				
Suspension data				
Attendance data				
Parent survey data				
Teacher survey data				

14) Training and preparation in data-driven decision-making

To what extent have you received effective training or support in data-driven decision-making in the following settings?

	None at all	Only a little	Some	A lot
Undergraduate degree program	( )	( )	( )	( )
Graduate degree program (administrative credential)	( )	( )	( )	( )
Teacher preparation program (credential program)	( )	( )	( )	( )
School district sponsored staff development	( )	( )	( )	( )
Professional conferences	( )	( )	( )	( )
Site level staff development	( )	( )	( )	( )
Team level collaboration	( )	( )	( )	( )

Teacher Behaviors

Part IV: This questionnaire is designed to provide a profile of teacher behaviors in data-driven decision-making. It consists of several behavioral statements that describe teacher data-driven decision-making practices and behaviors. You are asked to consider each question in terms of your perception of teachers behaviors over the past school year.

Read each statement carefully. Then click the option that best fits their job behavior or practice during the past school year. In some cases, these responses may seem awkward; use your judgment in selecting the most appropriate response to such questions. Try to answer every question. Thank you.

15) Teacher Behaviors in Data Use

How frequently do your teachers use student data to...?

	1 Never	2	3	4	5 All the time
Set individual student improvement goals and targets	( )	( )	( )	( )	( )
Set class improvement goals and targets	( )	( )	( )	( )	( )
Analyze aggregate data with other teachers to inform joint action in meeting student needs	( )	( )	( )	( )	( )
Tailor instruction for the whole class	( )	( )	( )	( )	( )
Divide students into small groups to provide interventions	( )	( )	( )	( )	( )
Change instructional strategies for individual students	( )	( )	( )	( )	( )
Identify students to target for intervention	( )	( )	( )	( )	( )

Principal Behaviors

Part III: This questionnaire is designed to provide a profile of principal leadership in data-driven decision-making. It consists of several behavioral statements that describe principal leadership practices and behaviors. You are asked to consider each question in terms of your self reflection regarding your leadership over the past school year.

Read each statement carefully. Then click the option that best fits the specific job behavior or practice of this principal during the past school year. In some cases,

these responses may seem awkward; use your judgment in selecting the most appropriate response to such questions. Try to answer every question. Thank you.

16) Expectations Regarding Data-Driven Decision-Making

Please indicate your agreement with the following statement:
I expect teachers in the school to use data to make decisions about instruction.

( ) Strongly disagree

( ) Disagree

( ) Neither disagree nor agree

( ) Agree

( ) Strongly Agree

17) Principal Leadership Style

How often do you . . . ?

	1 Never	**2**	**3**	**4**	**5 All The Time**
Develop and implement a joint vision with the staff regarding and purposes and aspirations of the school	( )	( )	( )	( )	( )
Set and monitor sitewide goals for student outcomes with staff	( )	( )	( )	( )	( )
Empower staff in instructional decision making in regards to curriculum and pedagogical strategies	( )	( )	( )	( )	( )
Evaluate and implement professional development plans with site staff	( )	( )	( )	( )	( )
Make decisions with site staff	( )	( )	( )	( )	( )

regarding the allocation of financial resources					
Encourage a commitment to shared accountability for student outcomes from all staff	( )	( )	( )	( )	( )

18) Principal Data-Driven Leadership Behaviors

How often do you . . . ?

	1 Never	**2**	**3**	**4**	**5 All the time**
Ask questions about teachers' past experience with using student data to inform decision-making	( )	( )	( )	( )	( )
Designate time during collaboration or shared planning for data analysis or decision-making	( )	( )	( )	( )	( )
Lead analyses of school or classroom data with site staff	( )	( )	( )	( )	( )
Demonstrate the process of making instructional decisions in response to data	( )	( )	( )	( )	( )
Observe and provide direct feedback of teacher practices in analyzing and using data	( )	( )	( )	( )	( )
Engage in dialogue with teachers regarding their process of data analysis or instructional decision making	( )	( )	( )	( )	( )

Encourage connections with other individuals with expertise (data analysis or pedagogical) that improves teachers' ability to utilize data	( )	( )	( )	( )	( )

District Office Behaviors

Part IV: This questionnaire is designed to provide a profile of district leadership in data-driven decision-making. It consists of several behavioral statements that describe district leadership practices and behaviors. You are asked to consider each question in terms of your observations of the district's leadership over the past school year.

Read each statement carefully. Then click the option that best fits the specific job behavior or practice of your district leadership during the past school year. In some cases, these responses may seem awkward; use your judgment in selecting the most appropriate response to such questions. Try to answer every question. Thank you.

19) Expectations Regarding Data-Driven Decision-Making

Please indicate your agreement with the following statement:
School district leadership expects teachers in the school to use data to make decisions about instruction.

( ) Strongly disagree

( ) Disagree

( ) I don't know what district leadership expects in regards to data use

( ) Agree

( ) Strongly agree

20) District Leadership Support Behaviors
How often does district leadership...

	1	**2**	**3**	**4**	**5**

	Never				All the time
Provide expertise on data use through central office personnel	( )	( )	( )	( )	( )
Set expectations for data use in school improvement	( )	( )	( )	( )	( )
Provide supplementary technological or other tools for facilitating data use	( )	( )	( )	( )	( )
Develop expertise through professional development to meaningfully incorporate data use into decision making	( )	( )	( )	( )	( )
Collect district and state assessment information and provide it in a timely fashion for sites	( )	( )	( )	( )	( )

21) Local Control Accountability Plan

The new system of school funding known as the Local Control Funding Formula has created a new system of planning and accountability in California. One key part of this system is the Local Control Accountability Plan, which is adopted by the school district on an annual basis. How much knowledge **do you have regarding the following elements of the Local Control Accountability Plan?**

	None at all	Only a little	Some	A lot
LCAP Goals for the School District	( )	( )	( )	( )
LCAP Actions and Services for All Students	( )	( )	( )	( )
LCAP Actions and Services	( )	( )	( )	( )

for Low Income Students				
LCAP Actions and Services for English Learners	( )	( )	( )	( )
LCAP Actions and Services for Foster Youth	( )	( )	( )	( )
LCAP Metrics/Annual Measurable Outcomes	( )	( )	( )	( )

22) <u>How much effect</u> has the Local Control Accountability Plan had on your practice as a site leader in the following areas in the last year? If you have no option, please select "Not Applicable".

	Completely Negative 1	**Very negative 2**	**Somewhat Negative 3**	**Neither Negative nor**	**Positive 5**	**Very Positive 6**	**Completely Positive 7**	**Not Applicable**
Data-driven decision-making practices	( )	( )	( )	( )	( )	( )	( )	( )
Student curriculum	( )	( )	( )	( )	( )	( )	( )	( )
Intervention programs for at-risk students	( )	( )	( )	( )	( )	( )	( )	( )
Classroom Instructional strategies	( )	( )	( )	( )	( )	( )	( )	( )
School discipline/behavior systems	( )	( )	( )	( )	( )	( )	( )	( )
School Site Budgets	( )	( )	( )	( )	( )	( )	( )	( )

Personnel Decisions	( )	( )	( )	( )	( )	( )	( )	( )

23) District Leadership Behaviors

Are there any other ways in which district leadership either supports the use of Data-Driven Decision-Making which was not included above? Are there other things the district does that makes it difficult for you to engage in Data-Driven Decision-Making? Please use the space below to describe.

____

____

____

____

Thank You!

Thank you for participating in this study. Your response is very important to us.

Appendix C - LCAP Outcomes for Principal Survey

Table C1

Average Difference Score on Question Regarding LCAP Knowledge

question	A	B	C	E	F	H	I	J	K	ALL
t23lcapknow_actsall	0.55	1.37	1.17	0.76	2.04	1.87	1.00	2.18	1.22	1.46
t23lcapknow_actsel	0.55	1.33	1.12	0.82	2.20	1.87	1.32	1.90	1.87	1.51
t23lcapknow_actsfy	1.05	1.37	1.17		2.25	2.12	1.12	1.73	1.66	1.64
t23lcapknow_actsli	0.63	1.33	1.12	0.76	2.10	2.03	1.12	1.87	1.87	1.49
t23lcapknow_goals	1.26	1.18	1.17	0.76	2.14	1.97	1.32	2.03	1.50	1.54
t23lcapknow_metrics	1.05	1.37	1.32		1.26	1.06	0.87	2.26	1.66	1.39
ALL	0.89	1.33	1.18	0.78	2.03	1.85	1.14	2.01	1.65	

Note: actsall=All LCAP actions, actel =English Learner actions, actsfy=Foster Youth action, actsli=Low income actions

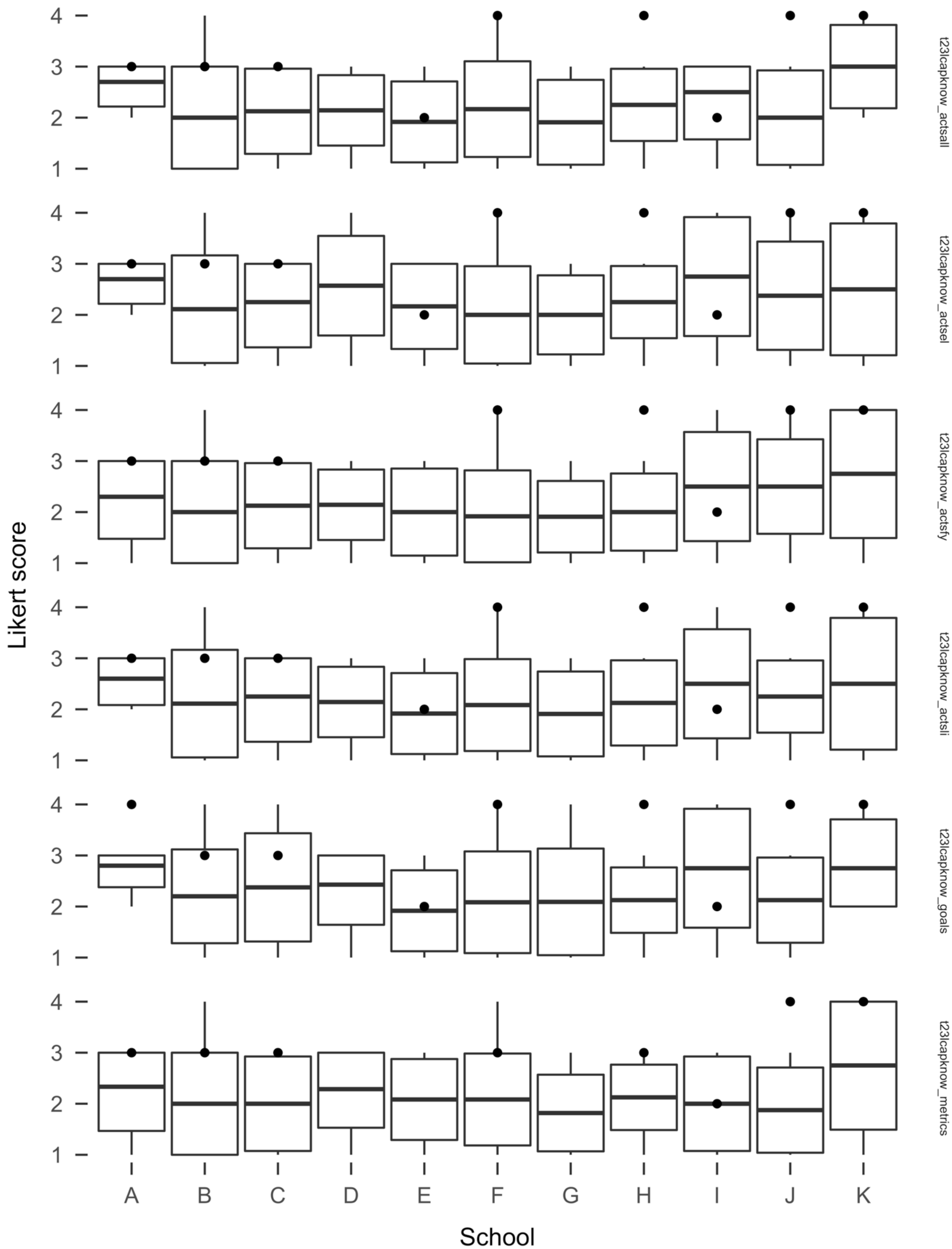

Figure C1. Plot of Teacher and Principal Responses Regarding LCAP Knowledge

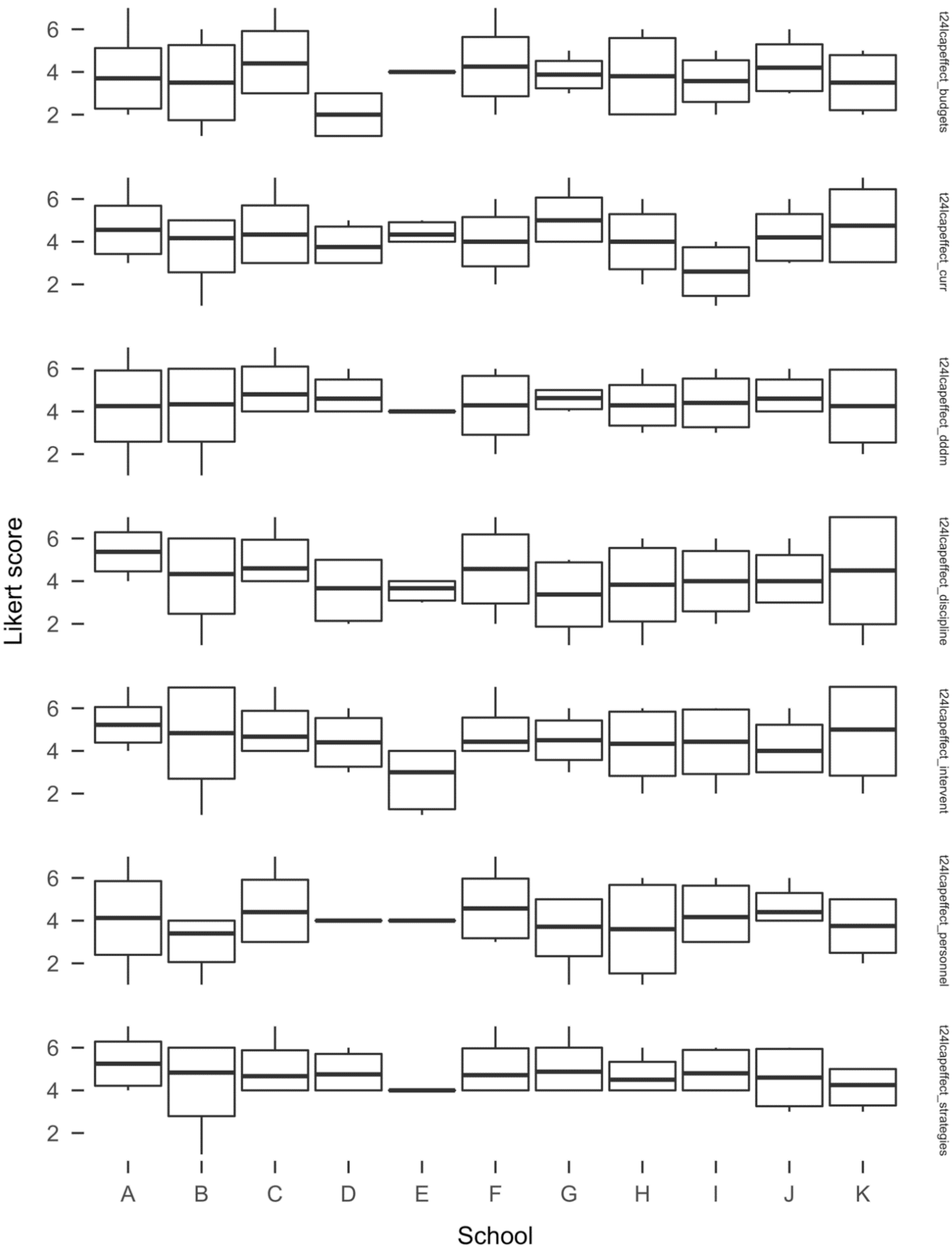

Figure C2. Plot of Teacher Responses Regarding LCAP Effect

Appendix D - Correlation Tables for Survey Questions

Table D1

Polychoric correlation of variables describing frequency of use of differing types of data

	t11often_state	t11often_el	t11often_dist	t11often_bench	t11often_susp	t11often_att	t11often_parent	t11often_teacher
t11often_state	1.00							
t11often_el	0.53	1.00						
t11often_dist	0.09	0.25	1.00					
t11often_bench	-0.51	-0.11	0.20	1.00				
t11often_susp	0.53	0.24	0.05	-0.11	1.00			
t11often_att	0.24	0.15	0.07	0.03	0.20	1.00		
t11often_parent	0.24	0.11	-0.06	-0.04	0.40	0.27	1.00	
t11often_teacher	-0.17	0.06	-0.08	0.06	0.34	0.14	0.64	1

Table D2

Polychoric correlation of variables describing difficulty of access of data

	t12diff_state	t12diff_el	t12diff_dist	t12diff_bench	t12diff_susp	t12diff_att	t12diff_parent	t12diff_teach
t12diff_state	1.00							
t12diff_el	0.57	1.00						
t12diff_dist	0.44	0.44	1.00					
t12diff_bench	0.21	0.27	0.61	1.00				
t12diff_susp	0.31	0.16	0.35	0.10	1.00			
t12diff_att	0.28	0.33	0.33	0.33	0.18	1.00		
t12diff_parent	0.25	0.23	0.29	0.21	0.68	0.27	1.00	
t12diff_teach	0.22	0.15	0.30	0.26	0.66	0.26	0.84	1

Table D3

Polychoric correlation of variables describing expertise in use of data

	t13expert_state	t13expert_el	t13expert_dist	t13expert_bench	t13expert_susp	t13expert_att	t13expert_parent	t13expert_teacher
t13expert_state	1.00							
t13expert_el	0.63	1.00						
t13expert_dist	0.19	0.30	1.00					
t13expert_bench	0.18	0.36	0.77	1.00				
t13expert_susp	0.56	0.32	0.00	-0.03	1.00			
t13expert_att	0.30	0.33	0.27	0.31	0.32	1.00		
t13expert_parent	0.40	0.34	0.17	0.24	0.58	0.55	1.00	
t13expert_teacher	0.36	0.33	0.26	0.35	0.46	0.51	0.82	1

Table D4

Polychoric correlation of variables describing relevance to goals

	t15rel2goals_state	t15rel2goals_el	t15rel2goals_dist	t15rel2goals_bench	t15rel2goals_susp	t15rel2goals_att	t15rel2goals_parent	t15rel2goals_teacher
t15rel2goals_state	1.00							
t15rel2goals_el	0.40	1.00						
t15rel2goals_dist	0.25	0.53	1.00					
t15rel2goals_bench	0.13	0.46	0.63	1.00				
t15rel2goals_susp	0.48	0.40	0.12	0.00	1.00			
t15rel2goals_att	0.55	0.40	0.12	0.03	0.48	1.00		
t15rel2goals_parent	0.39	0.31	0.28	0.15	0.47	0.47	1.00	
t15rel2goals_teacher	0.27	0.19	0.22	0.20	0.29	0.25	0.66	1

Table D5

Polychoric correlation of variables describing relevance to teacher evaluation

	t15rel2teacher_state	t15rel2teacher_el	t15rel2teacher_dist	t15rel2teacher_bench	t15rel2teacher_susp	t15rel2teacher_att	t15rel2teacher_parent	t15rel2teacher_teacher
t15rel2teacher_state	1.00							
t15rel2teacher_el	0.55	1.00						
t15rel2teacher_dist	0.52	0.72	1.00					
t15rel2teacher_bench	0.31	0.59	0.72	1.00				
t15rel2teacher_susp	0.51	0.48	0.50	0.36	1.00			
t15rel2teacher_att	0.55	0.56	0.39	0.38	0.60	1.0		
t15rel2teacher_parent	0.44	0.48	0.54	0.45	0.52	0.5	1.00	
t15rel2teacher_teacher	0.43	0.44	0.47	0.49	0.41	0.4	0.56	1

Table D6

Polychoric correlation of variables describing relevance to curriculum and instruction

	t15rel2ci_state	t15rel2ci_el	t15rel2ci_dist	t15rel2ci_bench	t15rel2ci_susp	t15rel2ci_att	t15rel2ci_parent	t15rel2ci_teacher
t15rel2ci_state	1.00							
t15rel2ci_el	0.29	1.00						
t15rel2ci_dist	0.21	0.60	1.00					
t15rel2ci_bench	0.19	0.38	0.47	1.00				
t15rel2ci_susp	0.28	0.24	0.11	-0.11	1.00			
t15rel2ci_att	0.07	0.16	-0.04	0.06	0.60	1.00		
t15rel2ci_parent	0.12	0.18	-0.01	0.09	0.44	0.44	1.0	
t15rel2ci_teacher	0.17	0.01	-0.06	0.18	0.02	-0.01	0.5	1

Table D7

Polychoric correlation of variables describing relevance to intervention

	t15rel2int_state	t15rel2int_el	t15rel2int_dist	t15rel2int_bench	t15rel2int_susp	t15rel2int_att	t15rel2int_parent	t15rel2int_teacher
t15rel2int_state	1.00							
t15rel2int_el	0.41	1.00						
t15rel2int_dist	0.23	0.57	1.00					
t15rel2int_bench	0.20	0.46	0.68	1.00				
t15rel2int_susp	0.11	-0.10	-0.07	-0.22	1.00			
t15rel2int_att	0.38	0.17	0.06	0.11	0.54	1.00		
t15rel2int_parent	0.10	0.08	0.04	0.02	0.45	0.40	1.00	
t15rel2int_teacher	0.10	0.04	0.07	0.14	0.32	0.28	0.67	1

Table D8

Polychoric correlation of variables regarding frequency of use of data

	t17freqndgoals	t17freq_classgoals	t17freq_aggregate	t17freq_whole	t17freq_smallgroup	t17freqndstud	t17freqnter
t17freq_goals	1.00						
t17freq_classgoals	0.67	1.00					
t17freq_aggregate	0.44	0.39	1.00				
t17freq_whole	0.53	0.63	0.54	1.00			
t17freq_smallgroup	0.47	0.51	0.45	0.49	1.00		
t17freq_stud	0.47	0.42	0.43	0.58	0.65	1.00	
t17freq_inter	0.58	0.51	0.36	0.48	0.67	0.61	1

Table D9

Polychoric correlation of variables describing principal leadership style

	t19style_vision	t19style_goals	t19stylenst	t19style_pdplans	t19style_finance	t19style_account
t19style_vision	1.00					
t19style_goals	0.70	1.00				
t19stylenst	0.55	0.49	1.00			
t19style_pdplans	0.67	0.59	0.54	1.00		
t19style_finance	0.52	0.46	0.44	0.51	1.00	
t19style_account	0.72	0.55	0.60	0.65	0.53	1

Table D10

Polychoric correlation of variables describing principal DDDM leadership behaviors

	t20behavior_past	t20behavior_time	t20behavior_lead	t20behavior_demonstrate	t20behavior_feedback	t20behavior_dialogue	t20behavior_connect
t20behavior_past	1.00						
t20behavior_time	0.55	1.00					
t20behavior_lead	0.56	0.66	1.00				
t20behavior_demonstrate	0.64	0.64	0.75	1.00			
t20behavior_feedback	0.63	0.53	0.60	0.67	1.00		
t20behavior_dialogue	0.62	0.55	0.65	0.74	0.70	1.00	
t20behavior_connect	0.55	0.55	0.67	0.66	0.64	0.71	1

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