HOW TECHNOLOGY, STRATEGIC DECISION MAKING, AND SCHOOL CONTEXT INFLUENCE PRINCIPALS' USE OF A DATA WAREHOUSE: A LATENT CLASS GROWTH ANALYSIS

By

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To those who matter most—

Nicole, Maci, Esther, and Owen

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LIST OF ABBREVIATIONS

DDDM Data-Driven Decision Making

EL English Learner

ESEA Elementary and Secondary Education Act

FRPL Free-Reduced Price Lunch

ICTs Information and Communications Technologies

INI In Need of Improvement Status (under NLCB)

ISLLC Interstate School Leaders Licensure Consortium

LCGA Latent Class Growth Analysis

LDV Limited Dependent Variable Model

LEA Local Educational Agency

MAR Missing at Random

NCLB The No Child Left Behind Act of 2001

OR Odds Ratios

RRR Relative Risk Ratios

RttT Race to the Top

SMHC The Strategic Management of Human Capital

SPED Special Education

TVA Teacher Value-Added

VALED Vanderbilt Assessment of Leadership in Education

VPN Virtual Private Network

CHAPTER I

INTRODUCTION

Data-driven decision making (DDDM), or simply "data use," has been described as "one of the most prominent strategies for educational improvement in the country" (Coburn and Turner, 2012, p. 100). At the Federal level, the American Reinvestment and Recovery Act, along with the Statewide Longitudinal Data Systems Grants Program and the Common Education Data Standards, have promoted and backed data use initiatives (Congress, 2009; Means et al., 2010); private foundations, including the Bill and Melinda Gates Foundation, the Stupski Foundation, and the Spencer Foundation, have supported work examining the processes, contexts, and factors that affect organizational data use (Wayman and Stringfield, 2006; Turner et al., 2012); and a host of peer-reviewed journal articles, policy reports, and how-to guidebooks have touted the benefits of using data for school improvement (Mandinach, 2012; Goldring and Berends, 2008; Love, 2008; Earl and Katz, 2002).

Implicit in this work is the belief that data use is a necessary skill of effective school leaders—a "must-have" requirement of the 21st Century leader (Earl and Katz, 2002). In fact, education leadership policy and program standards and newly developed principal evaluation tools define and assess competencies associated with school leaders' use of student assessment and demographic data (Licensure, 2008; Wilmore, 2002; Murphy et al., 2011). Thus, while principals are supposed to play a critical role in successfully implementing data use initiatives (Schildkamp and Kuiper, 2010; Wohlstetter et al., 2008; Ikemoto and Marsh, 2007; Wayman et al., 2006), there is a general lack of understanding surrounding their use of data (Datnow et al., 2007; Means et al., 2010). This gap in the literature seems particularly salient given that principals now have access to more varied types and sources of data, including information on teacher performance and stakeholder perception, that have the potential to change their instructional and human capital decision making (Kane et al., 2013; Goldring et al., 2015; Donaldson, 2013; Cohen-Vogel, 2011).

Concurrent with access to newer and more varied types data has been significant investments in technology to support data use. One recent estimate suggests that the U.S. Department of Education has invested more than $610 million to build the technological infrastructure for data collection, storage, and analysis (Mandinach et al., 2012). Additionally, notable changes in the variety, volume, and velocity of data (Laney, 2001) available to schools and school districts has fueled efforts to build technological platforms, data systems, and tools to support data use. Investments in these tools and data systems is not insignificant—a recent estimate suggests that venture funding for institutional and learning analytics has grown 687% from 2012, totaling $58 million in the first three quarters of 2014 (Murali, 2014). Moreover, a survey of school districts finds that educational data systems are widespread, with nearly 80 percent reporting that they have an assessment system that organizes and analyzes benchmark assessment data and a data warehouse that provides access to current and historical data on students as well as data on other aspects of district functioning (Means et al., 2010). These systems' rapid growth and popularity notwithstanding, I find that there has been no systematic examination of the ways in which principals use these types of data systems in their everyday practice.

I.1 Purpose and Research Questions

Therefore, in this dissertation I examine how principals in a large, urban school district use data by exploring how they access information on a district-developed Data Warehouse during an academic school year. I define the Data Warehouse as a Web-based, centralized location where principals can access data reports on student achievement; student attendance, behavior, and discipline; and teacher performance, including value-added scores. Because my conceptualization of principals' data use is mediated by technology (i.e., the Data Warehouse), it is important to account for the presence of heterogeneous subpopulations of technology users—that is, heterogeneous groups of principals who vary in their dispositions to use technology. Recent evidence from a nationally representative sample of U.S. adults suggests that principals may fall into one of at least three broad classes of technology users (Horrigan, 2007). Thus, to empirically examine for the presence of unique sub-populations of principals' Data Warehouse use, I utilize a latent class growth analysis (LCGA) to define heterogeneous sub-group trajectories of principals' monthly logins to the Data Warehouse. I ask:

RQ1. Are there significantly different types of Data Warehouse users among principals?

Along with determining the presence of distinct sub-groups of Data Warehouse users, I explore the extent to which subgroup differences might be explained by three factors: (1) technology and technology use; (2) principals' strategic human capital decision making; and (3) school accountability and organizational context.

Technology and technology use

Differences in principals' Data Warehouse use may be attributable to their own personal inclinations to use or not use technology. Research in the information systems literature suggests that age and gender are important moderators of information and communications technology (ICT) use in organizational settings (Gefen and Straub, 1997; Venkatesh and Davis, 2000; Venkatesh et al., 2003). In addition, individual principals may vary in their perceptions of the value, functionality, and utility of the Data Warehouse itself. For example, principals who find that the Data Warehouse offers them tools for accessing, organizing, and analyzing data in ways they previously could not may be more inclined to use the system over time. In short, sub-group differences in Data Warehouse use may be captured by examining the relationships between different patterns of Data Warehouse use and individual preferences, dispositions, and affinities for technology and/or for the Data Warehouse itself. Using data from a survey of principals in the district

I ask:

RQ2. How do principals' personal inclinations to use technology and/or their views of the Data Warehouse distinguish types of Data Warehouse users?

Principals' strategic human capital decision making

Explaining differences in Data Warehouse use by technology alone, however, fails to account for the fact that principals use the system to access information on students and teachers, information that is the "lifeblood" of a new movement in education oriented around the strategic management of human capital (SMHC) (Kimball, 2011). SMHC focuses on anchoring human capital processes such as recruitment and staffing strategies, induction, professional development, evaluation, and compensation in the instructional vision of the school and district (Odden, 2011b). To do so, school leaders draw heavily upon performance information on students and teachers to inform their human capital decision making. Recent work suggests that some principals are beginning to use new teacher evaluation processes and data to inform decisions regarding teacher hiring, assignment, and dismissal (Goldring et al., 2015; Drake et al., 2014a), although there are still many economic, contractual, cultural, and interpersonal barriers that principals face in doing so (Donaldson, 2013). Thus, variation in principals orientation towards data use for human capital decision making and/or their perception of the barriers in doing so may contribute to subgroup differences in Data Warehouse use. As a result, I ask:

RQ3. How does principals' orientations towards data use for strategic human capital decision making distinguish types of Data Warehouse users?

School accountability and organizational context

Along with principals' personal dispositions to use technology, their views of the Data Warehouse, and their use of data for strategic human capital decision making, principals work within organizational contexts and under accountability pressures that may influence the ways in which they use data. High stakes accountability has not only produced more formative and summative performance data, but also incentives to use the data to meet accountability standards (Firestone and González, 2007; Marsh, 2012). Since this accountability pressure varies by school performance, principals in lower performing school settings may have greater incentives to use the data (Diamond and Cooper, 2007; Fusarelli, 2008). In addition, research on how professionals seek out and use information suggests that individuals' information needs vary based on their organizational contexts and environments (Leckie et al., 1996). For example, principals with larger or more diverse student bodies may use the Data Warehouse in systematically different ways than their peers in smaller or more homogenous settings. There is also some evidence that suggests that the success of data use interventions and the use of data systems varies by school level (Carlson et al., 2011; Shaw and Wayman, 2012). Thus, principals' patterns of Data Warehouse use may be influenced by external factors related to accountability and organizational context. Accordingly, I ask:

RQ4. How does school accountability and organizational context distinguish types of Data Warehouse users?

CHAPTER II

LITERATURE REVIEW & CONCEPTUAL FRAMEWORK

II.1 The Principalship, School Accountability, and Principal Data Use

During the past few decades, the field of educational administration has transitioned from a model of school leadership based largely on private-sector management and behavioral science to one that has reshaped and reoriented the profession to focus on student learning, school improvement, school-community relations, and social justice (Murphy, 2005). With this reorientation, principals are now called upon to fulfill a variety of functions and roles beyond their traditionally assigned role of adhering to ethical norms and managing school operations (Terosky, 2013), including promoting a child-centered vision of high quality schooling and high quality instruction; monitoring curricula and assessment; creating an inclusive professional community and culture of care for students and teachers; engaging with families, communities, and other external stakeholders; and developing an equitable and culturally responsive school (Murphy, forthcoming). [1]

Along with this reorientation towards learning, improvement, engagement, and justice has been an increased emphasis on teacher quality, the most important in-school factor in explaining variation in student performance (Aaronson et al., 2007; Rivkin et al., 2005; Rockoff, 2004). Support from both public (e.g., Race to the Top) and private (e.g., Bill and Melinda Gates Foundation) initiatives has helped create new teacher evaluation systems designed to better capture variation in teacher effectiveness. In general, these systems include measures of classroom practice, teacher value-added and student growth, and stakeholder perception (Kane et al., 2013). Importantly, new teacher evaluation systems also demand a lot of principals' time and attention, especially with regards to the many formal and informal classroom observations they are required to conduct for all

[1] These roles and functions are primarily drawn from the latest Interstate School Leaders Licensure Consortium (ISLLC) standards (2014). For more information on the development of these standards, see Murphy (forthcoming).

their teachers each school year (Donaldson, 2013; Goldring et al., 2015) . They also figure prominently in new management principles designed to orient the profession around the strategic management of human capital, which includes the strategic hiring, assignment, development, retention, and dismissal of teachers (Grunow et al., 2012; Kimball, 2011; Odden, 2011a).

Furthermore, this reorientation towards student learning, teacher evaluation, and strategic human capital management has occurred alongside and within a national accountability and standards movement, the most well-known product of which is the No Child Left Behind Act of 2001 (NCLB), or the federal reauthorization of the Elementary and Secondary Education Act (ESEA) that requires local educational agencies (LEAs) produce and disseminate an annual report card of achievement, including information on assessment, accountability, and teacher quality. Due to the enormous data requirements of NCLB, states and districts throughout the country have worked to develop their information technology infrastructure (Thorn et al., 2007) and formulate processes and procedures for inquiring into the quality of their educational program (Copland, 2003; Knapp et al., 2007). In response, a host of private providers have flooded the education market with data warehousing, dashboard, and analysis tools promising to meet the data needs of schools and districts—a multimillion dollar industry that continues to grow larger each year (Murali, 2014; Laney, 2001).

Importantly, both the expanded definition of the principalship and the accountability and standards movement have created a strong incentive for school leaders to become data literate; that is, to acquire the relevant knowledge and skills to analyze data to inform their work (Mandinach et al., 2012; Wayman et al., 2006). In fact, new school leader policy and evaluation standards define and assess competencies associated with data use—competencies that cut across and are embedded in the many different work-roles of principals (Knapp et al., 2007). For example, four of the six 2008 Interstate School Leaders Licensure Consortium (ISLLC) standards include specific functions associated with data collection, monitoring, and use, including (a) collecting and using data to identify goals, assess organizational effectiveness, and promote organizational learning (Standard 1.B); (b) developing assessment and accountability systems to monitor student progress (Standard 2.E); (c) collecting and analyzing data and information pertinent to the educational environment (Standard 4.A); and (d) assessing, analyzing, and anticipating emerging trends and initiatives in order to adapt leadership strategies (Standard 6.C). Similarly, the Vanderbilt Assessment of Leadership in Education (VALED) requires that principals monitor school improvement processes by systematically collecting and analyzing data to make judgments that guide decisions and actions, particularly with respect to monitoring student behavior and learning, the quality of instruction, the rigor of curriculum programs, and parental involvement (Porter et al., 2006; Murphy et al., 2011).

Importantly, principals' data use seems to respond to and be shaped by the accountability context in which the schools reside (Firestone and González, 2007; Fusarelli, 2008). Diamond and Cooper (2007) provide some insight into the way in which school status in a ranked accountability system influences data use, suggesting that, while not causal, "external pressures create an accountability context in which data use is different from that of higher performing schools that are not under such pressure" (p.250). Others suggest that data use for high stakes accountability creates incentives to misuse and/or abuse data (Heilig and Darling-Hammond, 2008; Ravitch, 2011), citing qualitative evidence that schools under NCLB in need of improvement (INI) status have been found to target "bubble-kids" at or near test score cut-offs in order to raise achievement (Au, 2007; Booher-Jennings, 2005).

Yet examples in the research literature on principals' data use and the ways in which it may be shaped by school accountability contexts is notably thin. Instead, studies on school leaders' data use tends to describe the strategies principals use to support faculty data use rather than a description of their own data use practices (Schildkamp and Kuiper, 2010; Wohlstetter et al., 2008; Ikemoto and Marsh, 2007; Wayman et al., 2006). Within this literature, however, we find a few examples of principals using data in their own work, including: principals modeling data use practices for teachers (Wayman et al., 2012; Lachat and Smith, 2005); principals disaggregating formative assessment and state student achievement data down to the classroom level by hand in order to distribute performance information to teachers (Datnow et al., 2007; Wayman et al., 2009); principals using student characteristics (e.g., ethnic and linguistic backgrounds; mobility; socioeconomic status) to help interpret school performance data (Anderson et al., 2010); principals examining why student sub-populations may be underperforming (Ikemoto and Marsh, 2007); and principals utilizing high-stakes test data to understand general patterns of performance, identifying class-, grade-, and school-wide strengths and weaknesses to plan professional development and other kinds of targeted interventions (Means et al., 2010; Mandinach et al., 2006). Other work in this area uses scholarly research to outline processes and procedures for using data. Streifer (2002) and Goldring and Berends (2008), for instance, describe school improvement processes that link data use practices to institutional mission and goals. In both, the authors provide information on the types of data to examine, techniques and procedures for analyzing data, and the different ways in which data and evidence can be used to make decisions.

Other research also examines the extent to which principals use teacher effectiveness data for strategic human capital decision making (Odden, 2011a; Kimball, 2011). For example, in a study of four school districts in Florida, Cohen-Vogel (2011) finds that all fifteen administrators in her sample of low and high performing schools reported using student achievement data to assign teachers to grades and subjects, though none reported using this information in tenured teacher dismissal decisions, preferring instead to "weed out" ineffective teachers before tenure. After the advent of new teacher evaluation systems, Donaldson (2013) finds that principals in her sample use classroom observation scores to place struggling teachers on performance improvement plans intended to prepare them for dismissal (Donaldson, 2013). In our own study of six urban school districts and two charter management organizations (CMO) in states that recently implemented new teacher evaluation models (Goldring et al., 2015), we find that principals use teacher effectiveness data to inform their human capital decision making, though this use varies greatly within and between systems. More generally, we find that teacher observation systems drive principals' use of data for teacher support, professional development, and, to a lesser extent, hiring, assignment, and dismissal (Cannata et al., 2014; Grissom et al., 2014; Drake et al., 2014).

Summary

In summary, principals' work has transitioned from a more narrow focus on school operations to a focus on student learning and teacher performance. This reorientation towards learning and performance appears to have shaped the ways in which principals use data on students and teachers to inform their instructional and human capital decision making. Further, the data-driven movement has been supported by both a national accountability and standards era and school leader policy and evaluation standards that assess competencies and skills associated with data use. Concurrently, districts and states across the country are spending millions of dollars developing the warehousing infrastructure and/or purchasing software products and data tools to support school and district data use (Easton, 2009; Wayman et al., 2004). Research on school leaders data and data systems' use, however, is notably thin. In particular, this research relies heavily on self-reported information from surveys and interviews of principals regarding their data use practices and does not empirically examine the relationship between data use and individual and organizational characteristics.

As a result, this dissertation explores principals' data use by using principals' access to a Data Warehouse during a school year to examine how principals cluster into homogenous sub-groups of data systems users, and the extent to which sub-group differences can be explained by individual and organizational characteristics. Specifically, I empirically examine how principals' dispositions to use technology; their views on the value, functionality, and utility of the Data Warehouse itself; their orientation towards strategic human capital decision making; the accountability pressure they are under; and their organizational environments and contexts distinguish types of data systems users.

Contribution

This dissertation contributes to the research literature in a number of ways. First, it begins to shed light on the extent to which the massive technology investment in data systems designed to store, organize, and present information on students and teachers is being utilized by principals in their everyday work. Despite the promises of technology to transform educational data use (Wayman et al., 2004), there is little to no objective information on how principals access information on data systems and how this access might vary in systematic ways (RQ1). Therefore, this dissertation is among the first to provide objective information on how often and when which principals use a data system during an entire school year.

Second, research on the use of information systems in organizational settings suggests that these systems are often under-utilized and produce relatively weak returns on their investment (Venkatesh and Davis, 2000; Sichel, 1997). By highlighting the relationships between technology and the types of Data Warehouse user (RQ2), I begin to examine if different utilization rates are associated with personal characteristics (i.e., age, technology aversion or affinity, gender) and/or system characteristics (i.e., design, functionality, perceived utility). The extent to which each of these is at play has important implications for districts wrestling with ways to increase utilization rates specifically, and data use more broadly.

Finally, a little over a decade's worth of research on data use in schools has not produced strong empirical evidence regarding the relationships between principals' strategic human capital decision making (RQ3), school accountability (RQ4), school context (RQ4), and their actual data use. Although accessing student and teacher reports is only part of a larger process of using data, the empirical analysis in this dissertation does provide a window into how each of these individual and organizational factors is associated with differences in the types of Data Warehouse users. Thus, it offers an important first glimpse at how these factors might contribute to differences in principals' data use practices more generally.

II.2 Conceptual Framework

Conceptualizing Technology Use

In order to begin to understand how principals might interact with and use the Data Warehouse during the school year, it may be helpful to describe the process of using the system. Principals have to turn on their computer, connect to a secure server, open the Internet, navigate to a login screen, and use their unique user name and password to login to the Data Warehouse, a user name and password that is different from the many other user names and passwords that they may be required to use in order to access other programs, including their email, state websites, and other private software and systems providers. If they are at home, the process requires them to first login to a Virtual Private Network (VPN), then proceed with the steps outlined above. Once they are logged into the system, principals are then presented with a list of reports contained on the system, a majority of which are static PDF documents, though the Data Warehouse does have a few reports which allow principals to sort and filter information to generate customized reports. Thus, there are **two** processes at work: the process of getting logged into the Data Warehouse and the process of navigating within the Warehouse to access reports.

For some principals, both processes may be second nature; for others, just sitting down at a computer may be the last thing they want to do; still others may be comfortable logging on to the Data Warehouse, but less confident navigating within the system to find data reports. The point is that principals' have their own personal inclinations, dispositions, skills, and preferences towards technology and technology use. In fact, the Pew Internet and American Life Survey, which polls a nationally representative sample of

U.S. adults, finds that individuals fall into one of three broad groups of technology users (Horrigan, 2007):

1. **Elite Tech Users**: Individual who are heavy and frequent users of the internet and cell phones and have strong positive views about how technology helps them do their job and learn new things;
2. **Middle-of-the-Road Tech Users**: Individuals whose outlook toward information technology is task-oriented and may find technology intrusive and information something of a burden; and
3. **Users with Few Tech Assets**: Individuals for whom modern gadgetry is at or near the periphery of their daily lives and who are generally content with old media.

Thus, for those principals who may be "Elite Tech Users," logging into and navigating within the Data Warehouse and other data systems will be both natural and instinctive; furthermore, as updates to the system are being made, including new data reports and/or functionalities, the elite users will be among the first to notice and explore them. They may also be among those that are most aware of the limitations of the Data Warehouse, including the types of information found there. Principals who are "Middle-of-the-Road Tech Users" may be drawn to the Data Warehouse because of it's utility in helping them perform the tasks required by their job, but they may find the processes of logging on and using the system somewhat burdensome. Principals who are among those users with "Few Tech Assets" are those for whom the technology itself and the process of navigating the system may be considered largely unnecessary given their preferences for old modes of accessing information and doing their job. Accordingly, accounting for the presence of these different users will be an important component of examining how principals might use the Data Warehouse in systematically different ways during the school year (RQ1).

Nonetheless, from an organizational management perspective, knowing that principals fall into different categories of technology users may not be as important as knowing how to identify reasons for these differences. Decades of research in the academic field of information sciences has explored and tested theoretical models of individuals' acceptance and use of technology in organizational settings (Fishbein and Ajzen, 1975; Ajzen, 1991; Davis, 1989; Thompson et al., 1991; Moore and Benbasat, 1991; Venkatesh and Speier, 1999). A wide array of applications across many professions and organizational settings finds that individuals' intentions to use information systems are often moderated by age and gender (Venkatesh et al., 2003). More specifically, while there seems to be a general consensus that age is negatively associated with information systems' use (Morris et al., 2005; Czaja et al., 2006), studies examining gender are not so conclusive (Venkatesh and Morris, 2000; Gefen and Straub, 1997). Research on teachers' use of computers and technology in the classroom finds no significant gender differences (Cuban et al., 2001; Marcinkiewicz, 1993).

Additionally, the information sciences literature finds that individuals' expectations regarding the systems' performance and its perceived ease of use will inform the extent to which individuals use information and communications technologies (ICTs) in their workplace settings (Davis, 1989; Venkatesh et al., 2003). For example, systems that are perceived as providing a relative advantage over previous modes of work (Moore and Benbasat, 1991); systems that are perceived in helping fulfill job performance expectations (Compeau and Higgins, 1995); and systems that help fulfill personal goals and expectations (Compeau et al., 1999) are more likely to be used than those that are perceived as less helpful (or even more burdensome) in executing job tasks. Moreover, systems that are perceived as being complex and difficult to understand are less likely to be used than those perceived as being easy to navigate and use (Thompson et al., 1991).

In short, variation in principals' inclinations to use technology and the Data Warehouse may be informed by both ascriptive characteristics (e.g., age, gender) and personal perceptions (e.g., performance expectancy, ease of use) (RQ2).

Strategic Data Use

Nevertheless, explaining different Data Warehouse user types with a technological framework alone fails to account for the fact that the Data Warehouse contains information on students and teachers that principals' may strategically use to inform their human capital decision making and/or respond to accountability pressures and common conditions found in their external organizational environment. That is, principals may use the Data Warehouse in systematically different ways because of similarities in their data use for managing teacher personnel decisions and/or similarities in the ways in which they respond to external pressures caused by accountability or differences in school context. Thus, within this conceptualization, differences in Data Warehouse use are less attributable to the technology itself and more attributable to individuals making strategic decisions to access the data contained there.

Strategic Decision Making. As outlined in the literature review, some principals appear to be using data from new teacher evaluation systems to inform their human capital and instructional decision making (Goldring et al., 2015; Cohen-Vogel, 2011). Central to these data use practices are the examination of student achievement and teacher performance data to inform decisions regarding teacher hiring, assignment, support, and dismissal (Odden, 2011a; Kimball, 2011; Cannata et al., 2014; Drake et al., 2014a). To explore whether Data Warehouse use is associated with strategic human capital decision making, I might examine if principals' own reports of their data use for strategic human capital decision making or their perception of the barriers they must overcome to use these data varies by type of Data Warehouse user. One strength of this method is that it can specifically address the topic of data use for human capital decision making; a weakness, however, is that principal reports may be biased due to social desirability and/or improper recall (Rossi et al., 2013). Thus, another method would be to examine when and what types of reports principals access on the Data Warehouse. Figure 1 provides a visual representation of when various kinds of student and teacher data are available in the

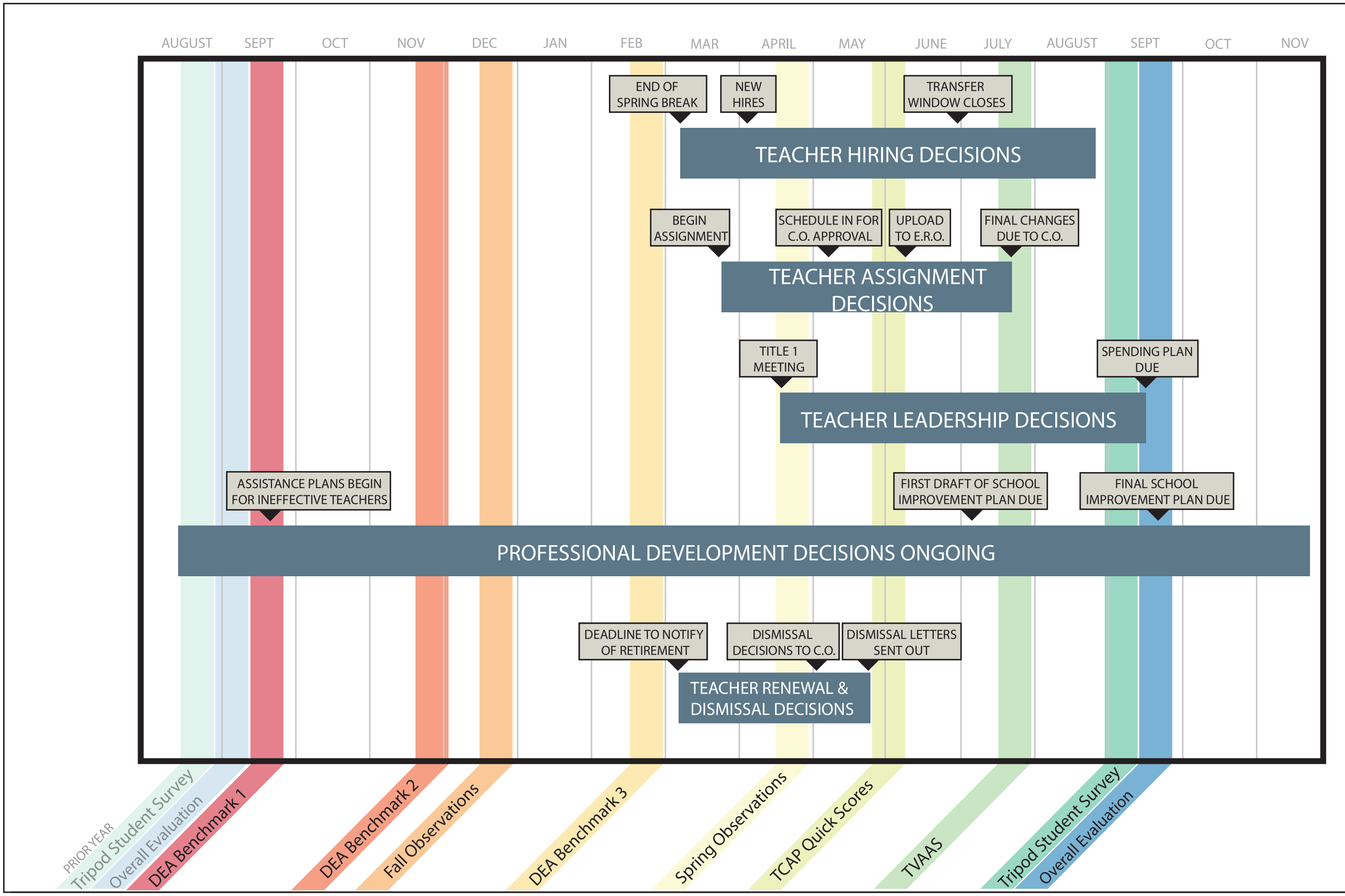

Figure 1: Timeline of Human Capital Decision Areas and Data Availability

district, as well as the timing of various human capital decision windows. Using this timeline for comparison, I could examine how and when different Data Warehouse user types access specific information in systematically different ways. Large differences during these human capital decision windows would then be suggestive of strategic data use. Used in combination, both asking principals to report on their data use for strategic decision making and examining their actual behaviors during the school year would provide a more complete picture of principals' use of the Data Warehouse to inform their human capital decision making.

Accountability. As reviewed above, the literature on school accountability and data use suggests schools under accountability pressures to improve performance or face high-stakes consequences like reconstitution tend to have incentives to interact with data in different ways than their counterparts in higher achieving school settings (Fusarelli, 2008; Diamond and Cooper, 2007; Firestone and González, 2007). Specific examples include teachers in low performing schools using data to target bubble-students or particular standards to improve student performance (Jennings and Bearak, 2014; Au, 2007; Booher-Jennings, 2005). In addition, district and state data systems grew up out of the accountability movement (Thorn et al., 2007; Wayman et al., 2004). As a result, their use is often closely associated with school assessment, accountability, and performance results (Anderson et al., 2010; Marsh, 2012). Accordingly, principals in lower performing schools may have an incentive to access information on student and teacher performance in systematically different ways than principals in lower performing schools, particularly with respect to the amount and type of information they access.

Yet "accountability" can relate not just to the pressures generated from state educational policies (e.g., NCLB), but to the many formal and informal means of motivating and holding administrators responsible for their performance (Marsh, 2012). In this regard, central offices leaders and supervisors fill the role of encouraging principal data use, often through joint examination of student achievement data (Goertz et al., 2009) and/or by holding principals accountable for their human capital decision making (Cohen-Vogel, 2011; Grissom et al., 2014). Importantly, new principal evaluations also include provisions that assess principals' data use, including the systematic collection and analysis of data to guide decisions and actions for continuous improvement (Clifford and Ross, 2011; Fuller et al., 2015; Murphy et al., 2011). Principals may also feel accountable for teacher performance on new teacher evaluation systems, leading some principals to monitor value-added, observation, and other information on teachers' performance (Goldring et al., 2015). Finally, principals may face informal accountability pressures through parental expectations for student achievement. In particular, principals in high performing schools often face pressures to maintain high levels of performance. Thus, principals in these schools may feel driven to monitor student and teacher performance in order to maintain high achievement levels.

School Context. Different formal and informal accountability pressures also highlight the different school environments and contexts principals work in. Research on the information seeking behavior of professionals suggests that principals' information needs are influenced by their organizational environment (Leckie et al., 1996). To clarify, information needs exist in the space between an individual's current knowledge and that knowledge which is needed to accomplish a given task (Case, 2012). In this way, they are unobserved and exist only in an individual's head (Belkin and Vickery, 1985). As a result, information needs must be inferred from actions individuals take to seek out and use information. Although this search process might have some social or intrinsic utility, professionals largely seek out information to accomplish their work (i.e., instrumental utility) (Bosman and Renckstorf, 1996). These information search processes seem to be heavily influenced by job role and organizational context (Leckie et al., 1996).

Decades worth of school effectiveness research has examined school context variables as it relates to student socioeconomic status, school grade configuration (i.e., school level), school governance structures, and community type (Teddlie and Reynolds, 2000).

Importantly, research as found that variations in school level contribute to different forms of principal leadership. Teddlie et al. (2000) argue that compared with elementary principals, "...it is probably impossible for a secondary principal to be an expert in all instructional areas covered by a secondary curriculum" (p.180). Heck (1992) finds that secondary principals spend substantially less time on key instructional tasks like observing classroom practices, promoting discussion about instructional issues, and emphasizing the use of test results for program improvement than do elementary school principals. These differences are at least partially attributable to the different size of the faculty, students, and staff between school levels, where middle and high school principals not only have more specialized subject matter, but also have larger student and faculty populations.

In addition, the effective schools' literature also suggests that principals work varies by student socioeconomic status (Teddlie and Reynolds, 2000). Hallinger and Murphy (1986), for instance, find that principals in low- and high-SES schools vary with regards to their control of instruction and task orientation. A few studies similarly find that principals in low-SES schools tend to "manage" teachers and instruction with more control, whereas principals in high-SES schools tend to "lead" schools through collaboration and vision (Mendez-Morse, 1992; Firestone and Wilson, 1989).

As a result, principals with different grade arrangements and with different student populations may use the Data Warehouse in systematically different ways throughout the school year than principals in elementary school settings. Although work on the relationship between school level and context and data use has not been empirically examined in the research literature (Mandinach et al., 2012), research examining the use of formative assessment data to improve student performance and teachers' use of a data dashboard both show variation by school level, although the reasons for these differences are unclear (Carlson et al., 2011; Shaw and Wayman, 2012).

Along with these more obvious characteristics of the school, a school's climate may also contribute to systematically different information needs and information seeking behaviors. Principals' work has been described as "hectic, fast-paced, and relentless" (Leithwood et al., 2010a, p.27). Along with the many tasks they are required to perform, their schools' facilities, organization, schedule, community support, and student conduct can vary dramatically and shape the time they have to use the Data Warehouse (Uline and Tschannen-Moran, 2008). For example, it seems reasonable to assume that schools whose physical environments are not well maintained or with a poor Internet connection; schools with little community support; and/or schools with student behavior problems may decrease the time which a principal has to use the Data Warehouse.

II.2.1 Summary of the Conceptual Framework

In this section, I hypothesize that differences in Data Warehouse user types may be associated with a number of factors (Table 1. These include: (a) technology and technology use, which has been found to be influenced by both ascriptive characteristics of individuals (e.g., age, gender) and perceptions of the expected performance and ease of use of the systems' themselves; (b) strategic human capital decision making, that may be captured in both principal self-reports and in the timing of when and how principals access information on students and teachers throughout the year; (c) school accountability and school context and climate, which includes student and school characteristics, as well as indicators of the condition of the school's physical environment, the community support, and student behavior.

Importantly, these factors are by no means exhaustive. In particular, there may be other reasons for systematically different use of the Data Warehouse among principals, including different training experiences and districts supports. Due to data limitations, however, these factors cannot be addressed in this study. Future work will build upon this dissertation by examining the relationship between these other factors and principals' data systems' use.

Table 1: Summary of Conceptual Framework

Technology and Technology Use	Age, gender, expected performance of the Data Warehouse, ease of use.
Strategic Human Capital Decision Making	Principal self-report of data use for human capital decision making; barriers; timing of when and how principals access information on students and teachers during the school year
School Accountability	Student achievement; informal accountability pressure from the central office
School Context & Climate	School and student characteristics; condition of the facilities, community support, student behavior

CHAPTER III

METHODOLOGY

III.1 Data

Data for this dissertation are drawn from one large urban school district in the southern United States. This district includes 163 schools serving over 80,000 students, 73% of whom come from economically disadvantaged backgrounds; 15% receive English language services; and 12% special education. The district invested about 20% of their Race to the Top (RttT) funds on developing their data systems capability, including the development of the Data Warehouse. In addition, training on data use and use of the Data Warehouse is offered in monthly principals' meetings, although interviews with principals and central office leaders suggests that these training sessions are short, demonstrative rather than participative, and inconsistent (Drake et al., 2014b). In addition to these meetings, the district has a dozen district-level data coaches to support teachers and principals in use of the Data Warehouse. As with other districts, however, data coaches in this district have large spans of control and are mainly deployed to support teachers' use of student data for instructional improvement (Marsh, 2012; Mandinach et al., 2012; Weiss, 2012). Interviews with a random sample of principals in the district suggests that data coaches mainly interact with instructional coaches and teacher-leaders (Drake et al., 2014b). Thus, while the district's central office leadership emphasize data use and data-driven decision making, interviews with and surveys of principals suggests that there is relatively little data use by principals for instructional and human capital decisions and low levels of central office support and/or accountability pressure for data use (Drake et al., 2014b).

For this paper, I use data from three sources: (a) principal Web logs to the district's Data Warehouse and the state's Teacher Value Added (TVA) website; (b) a principal survey examining their use of teacher effectiveness data for human capital decision making; and (c) publicly available school-level administrative and climate data.

Principal Web logs to the Data Warehouse

The district's Data Warehouse was initially funded by a mayoral initiative to reduce the number of students dropping out of district schools, though the district's RttT funds helped to expand the district's efforts. Development of the Warehouse began in 2009 with the goal of providing a common location for academic and non-academic student data, including student mobility, parental education and income level, and noticeable changes in the student's environment. In the fall of 2012, a central office leader who works close with the data warehouse noted that the "focus...[is] on the student data: attendance, discipline, grades, test scores. All of our state [and formative] assessment data are loaded in there."[1] Examples of reports include information on student demographics, attendance, behavior, benchmark test scores, grades, and state standardized test scores. Due to recent changes in district's orientation around strategic human capital management, information on teachers and their performance began to be integrated into the system during the 2012-2013 school year. Examples include information on teachers' value-added scores, student standardized test scores organized by teacher, and teacher attendance.

Currently, the Warehouse has over 200 reports that principals can access. Each time a principal logs onto the system using their unique username and password, an electronic timestamp is recorded with information on the report access and the time of day. A timestamp is encoded information identifying when a certain event occurred, usually providing a date and time of day (e.g., 7-1-2013 8:14:32 AM). These timestamps are recorded and stored in log files that can be accessed by system administrators. As part of this dissertation, I received the log files containing information on principals' logins during the 2013-2014 academic school year, starting on July 1, 2013 and running through

[1] Quotation from an interview we conducted as part of our larger project examining principals' use of teacher effectiveness data for human capital decision making (Fall, 2012) (see also, Goldring et al. (2015); Drake et al. (2014b) and principaldatause.org for more information.)

June 30, 2014.

Principal Access to the TVA Website

The TVA website provides teachers, administrators, and district leaders with information on student growth calculated from the state's standardized test. Value-added estimation strategies attempt to account for students' prior test scores in order to isolate the effect of a year's worth of education. Some models also "net-out" the effect of other factors that may influence student test scores, like innate intelligence, family background characteristics, and the influence of peers in order to calculate a teacher effect.

The TVA measure used in this study uses all of a student's past test scores to establish a projected growth score for the current year. After the end-of-year standardized test, students actual scores are compared to their projected growth. The website offers principals the opportunity to view value-added scores at the state, district, school, teacher, and individual student levels. In each case, principals can view growth measures by year and, when applicable, three year averages.

The site has also developed a number of visualization tools to help principals interpret the scores. Scores from one to five are color coded from dark red ("students made substantially less progress than the predicted standard for academic growth") to dark green ("students made substantially more progress that the predicted standard for academic growth"). Each score also includes a standard error, or the level of uncertainty surrounding the estimation. Principals can use a range of diagnostic tools to view scores by select student subgroups over time.

For this study, data from the TVA website include the number of times principals login to the website each month. Unfortunately, information on the reports and tools that they access and use while on the website are not available. Similarly, information on when (i.e., day; time of day) principals access the website during the month are not available. It is also important to note that while TVA information is pulled into the Data Warehouse so that principals can access the scores directly from the Data Warehouse without having to go to the website, the website offers a number of interactive features and data visualizations that are not accessible in the Data Warehouse.

Principal Survey on Teacher Effectiveness Data Use for Human Capital Decision Making

The survey data for this study come from a larger study examining principals' use of teacher effectiveness data for human capital decision making (Goldring et al., 2015)[2]. The survey was designed to ask principals questions about (1) their feelings towards the new teacher evaluation model and the measures it produces; (2) their data systems and data systems use; (3) their teacher effectiveness data use in general, as well as for specific human capital decisions, including teacher hiring, assignment, and dismissal; (4) the support and professional development they have received from the district; and (5) their perceptions of various barriers to using teacher effectiveness data for human capital decision making. The principal survey was distributed through an online platform (Qualtrics) starting on September, 30 2013, and closed one month later. A total of 110 principals serving in traditional school settings responded to the survey, representing a response rate of 84.0%.

School-level Administrative Data

Administrative data come from the state's department of education, and include school-level information on school type (i.e., elementary, middle, high, other); student enrollment; student racial/ethnic backgrounds; student free and reduced price lunch status; and student test score achievement on a variety of state- and nationally-normed standardized tests. These data come from the most recent release, or the 2012-2013 school year, a timeframe which reflects the data that would be available to principals using the data systems during the 2013-2014 school year.

[2]This survey was administered as part of a larger study on principals' teacher effectiveness data use for talent management decision making, with funding from the Bill and Melinda Gates Foundation. For more information, visit principaldatause.org

In addition, I utilize information from the Teaching, Empowering, Leading and Learning (TELL) Survey of teachers administered each year by the state's department of education. This survey was administered in the spring of 2014 and captures information on teachers' perceptions of their school's climate during the 2013-2014 school year. Specifically, teachers report on issues related to facilities and resources; community engagement and support; and student conduct. The survey had a 79.4% response rate.[3]

III.2 Sample & Missing Data

The sample includes all public school principals that worked in traditional school settings in the district during the 2013-2014 school year (n = 131 schools).[4] I used a combination of email and in person visits and obtained consent for the release of identifiable Data Warehouse login information from 82 principals (62.6% consent rate).

Missing Data

One of the concerns with only having identifiable information on 62.6% of the district's principals is that principals who did not consent may be signaling something about their data use practices during the school year that may bias the results. In particular, if principals in the non-consent group systematically use the Data Warehouse **less** than principals who consented, then my estimates of total use will be biased upwards. To examine this possibility, I obtained de-identified information on Data Warehouse use from the full population of principals from the district. Principals who consented were then identified, allowing for the examination of the differences in Data Warehouse use for the consent and non-consent groups. To perform this analysis, I regressed total data

[3] Results from schools with less than a 50% response rate were not included in the public use data file.

[4] Charter schools were excluded from the sample based on the different ways in which principals in these schools interact with data and data systems. For example, many principals rely on their own internally developed processes of data collection and analysis rather than the district's Warehouse. As evidence, only 129 principals of the 163 total principals in the district used the Data Warehouse at least once during the school year. Based on conversations with central office leaders, it was determined that a majority of these "non-users" were charter, special education, and adult education principals. As a result, all of these schools were eliminated from the analysis. Together, they represent about 20% of the total number of schools in the district.

systems' use on consent, and found the estimated coefficient to be non-significant and negative (-2.00; p = 0.30). This finding holds even after controlling for variations in monthly use. Importantly, while there appears to be no difference between the consent and non-consent groups, the direction of the estimate suggests that, if anything, principals in the non-consent group used the system **more** than principals in the consent group, which would imply that my estimates of Data Warehouse use will be biased downwards.

Since I am also examining the relationship between Data Warehouse use and key principal and school characteristics, it is also important to examine these differences by consent status in order to make sure the estimated relationships are not biased as well. Table 2 reports mean differences between these groups, by select characteristics. As evident from this table, the consent and non-consent groups are similar on every measure except one, where the consent group appears to have more high school principals (p = 0.06). As a result, if principals in high school settings use the Data Warehouse on average more than principals in other settings, the estimates on use will be biased upwards. Given the small number of high schools (in total) and the analysis of data warehouse use differences by consent status above, however, it would appear that this is not the case.

Table 2 also shows that there are missing data in some important school and principal characteristics. In particular, while I have complete data on school characteristics, there are missing data with respect to the school climate scale and principals' views on the data system and central office accountability. The number of principals with missing school climate information is equal by consent status (n = 3) and nearly equal with regards to the principal survey (consented: n = 11; non-consented: n = 12); nonetheless, given the smaller proportion of principals in the non-consented group, these numbers reflect a different rate in missing data on these variables.

In both cases it is important to explore the reason for the missingness. In the case of the school climate data, missing data were reflective of a low (< 50 %) teacher response rate to the TELL survey. Regarding the principal survey on data use and human capital decision making, it is unclear why principals did not respond. Given the fact that the true reasons for these missing data are unknown, I have decided not to assume that the missing data are missing at random (MAR). As such, I will not use multiple imputation in my analyses. Instead, due to the small sample size I will be reporting results from the largest available sample, with supplementary tables in the Appendix with only those principals with complete data (n=66) (see Section A.2).

III.3 Measures

Types of Data Warehouse Users

Given the longitudinal nature of the data, there are a number of ways to operationalize "Data Warehouse use" in order to determine if there are distinct types Data Warehouse users in the sample of principals (RQ1). First, it is important to get a sense of the distribution of total Data Warehouse use during the school year; that is, the number of times principals used the Data Warehouse during the school year. As with other count data, I find that total use has a positive skew, with a median of 126.5, a mean of 162.9, and a wide range in use from 1 (n=3) to 724 uses (n=1) (Figure 2). Since these numbers suggest that the median principal only uses the system about 2.4 times a week, I have decided to use the number of times a principal use the Data Warehouse each month as my unit of analysis.

In Figure 3, I provide two line charts: in chart A, I graph each principal's monthly use of the Data Warehouse from July, 2013 through June, 2014. In thinking about the process of identifying types of Data Warehouse users, chart A does not seem to reveal any identifiable patterns. In particular, while there are certain months that seem to be punctuated by more use than others (e.g., July, March, April), there does not seem to be any identifiable trends in use. In Chart B, I graph each principal's cumulative monthly use of the Data Warehouse to try to capture how their use develops and progresses over the school year. While there are a large majority of principals that group at the low end of

Table 2: Non-consent bias, by select principal and school characteristics

	Consent	N	Non-Consent	N
Enrollment	596.90	82	598.57	49
	(386.54)		(263.24)	
White (%)	0.35	82	0.38	49
	(0.24)		(0.23)	
African American (%)	0.48	82	0.46	49
	(0.26)		(0.25)	
Latino (%)	0.30	82	0.27	49
	(0.32)		(0.29)	
Math 3 yr average	49.91	68	49.58	43
	(8.96)		(9.31)	
Reading 3 yr average	47.47	68	46.84	43
	(10.47)		(10.46)	
ACT 3 yr average	16.91	18	20.30	4
	(1.83)		(4.16)	
Free-Reduced Lunch (%)	0.75	82	0.74	49
	(0.23)		(0.22)	
Limited English Proficient (%)	0.13	82	0.14	49
	(0.18)		(0.13)	
Special Education (%)	0.12	82	0.13	49
	(0.10)		(0.04)	
Data Systems Scale	2.78	71	2.77	38
	(0.39)		(0.35)	
Central Office Presence Scale	0.01	71	0.15	38
	(0.57)		(0.75)	
Time Scale	0.66	79	0.66	46
	(0.14)		(0.14)	
Facilities Scale	0.82	79	0.82	46
	(0.10)		(0.11)	
Community Support Scale	0.80	79	0.79	46
	(0.14)		(0.16)	
Student Conduct Scale	0.78	79	0.78	46
	(0.15)		(0.16)	
Leadership Scale	0.79	79	0.79	46
	(0.14)		(0.14)	
Professional Development Scale	0.79	79	0.78	46
	(0.10)		(0.11)	
Elementary	0.52	43	0.60	27
Middle	0.24	20	0.29	13
High	**0.16**$^{+}$	**13**	**0.04**	**2**

Notes: Author's calculations. Standard deviations in parentheses.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.10$

cumulative use, there seems to be variability that may be explained by the mixing of heterogenous sub-groups of Data Warehouse users. As a result, in order to examine if there are different types of Data Warehouse users, I operationalize principals' "Data Warehouse use" as the cumulative frequency count of principals' use each month during the 2013-2014 school year (Chart B).

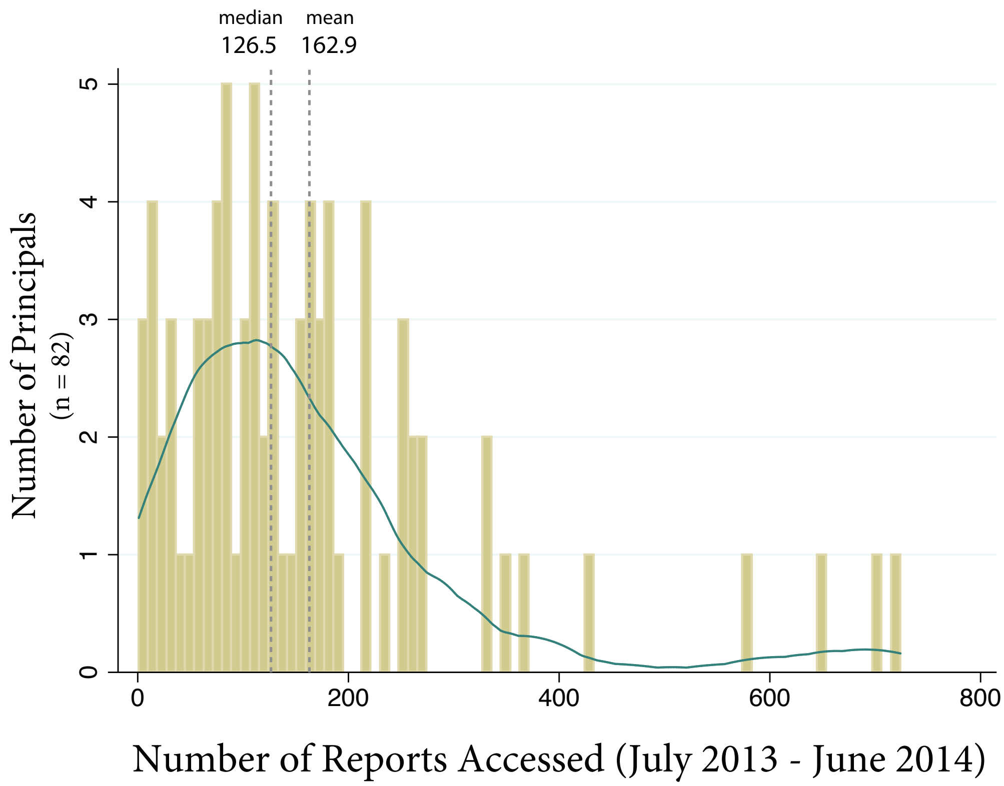

Figure 2: Distribution of Total Data Warehouse Use

Technology and Technology Use

As I outline in the conceptual framework (Section II.2; see also Table 1), principals' technological affinity and pre-dispositions to use technology will influence the ways in which they interact with the Data Warehouse. Measures that might account for this variation include generational differences (i.e., in age, experience), expected performance of the Data Warehouse, and ease of use. I also use a measure of principals' use of a parallel Web-based data system—the TVA website—to further account for their

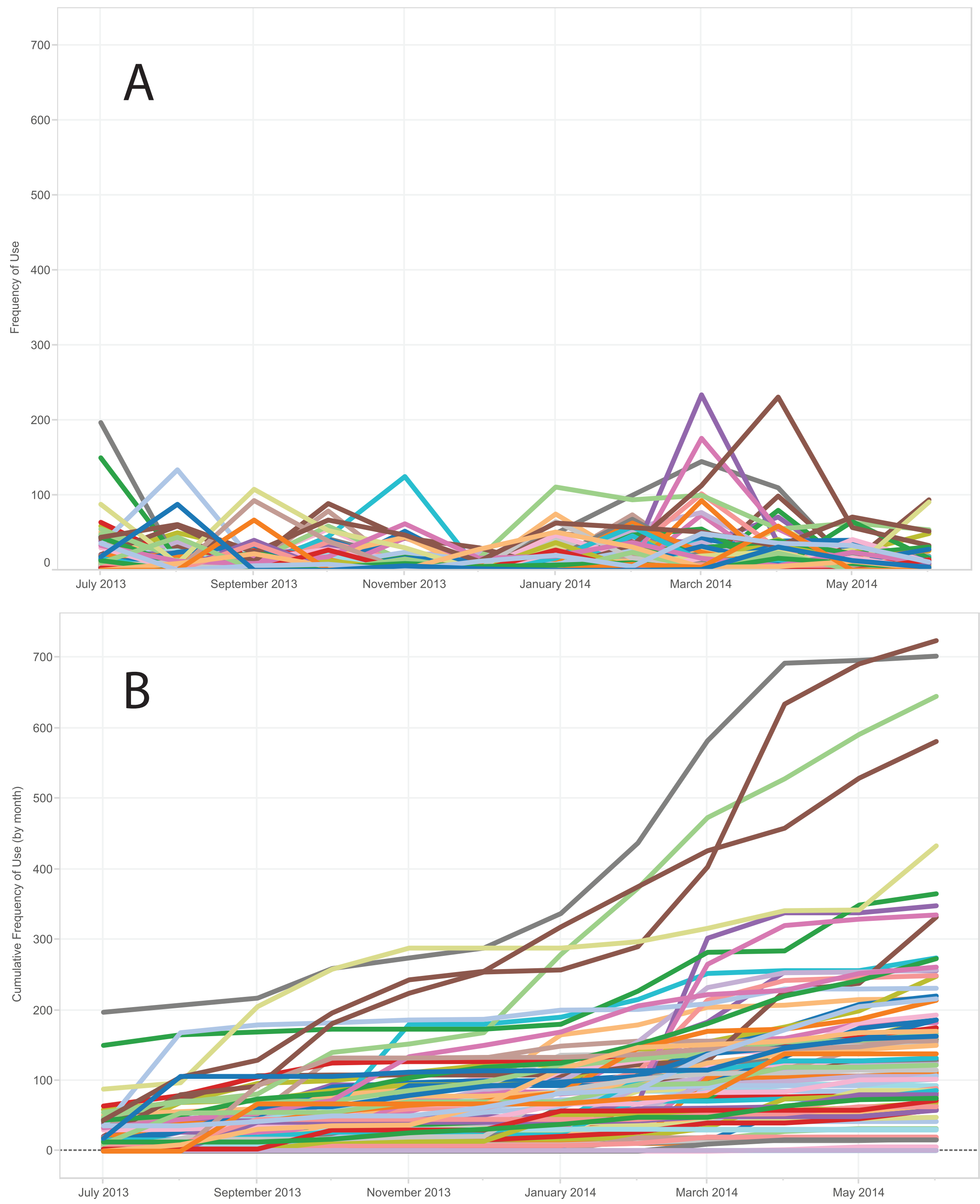

Figure 3: Frequency & Cumulative Frequency of Data Warehouse Use

preferences for technology and technology use.

Since I do not have a direct measure of principals' ages, I operationalize age with a measure of principals' total years of experience as a executive principal, making the assumption that principals' years experience will be positively correlated with their age. I recognize that total years' experience also captures principals' familiarity with the job of the principalship. Thus, any relationship between total years' experience and types of Data Warehouse user will confound these two constructs of age and experience. In my analytic sample, the median principal has 6 years of total experience as an executive principal, with a standard deviation of 6.3 years and a range of 1 to 22 years.

I operationalize gender as a binary dummy variable (female = 1). In this sample, 61% of the principals are female.

In order to operationalize principals' expectations regarding the performance of the Data Warehouse and its ease of use, I use a 12-item survey question from the Principal Survey on Teacher Effectiveness Data Use for Human Capital Decision Making. This question asks principals the following: "Based on your experience with your districts data dashboard,[5] to what extent do you agree or disagree with the following statements?", with a 4-item Likert scale ranging from ranging from "Disagree strongly" to "Agree strongly." The specific items are:[6]

1. The dashboard is straightforward to navigate (mean = 3.43, sd = 0.70).
2. The dashboard allows them to access data they could not access before (mean = 3.76, sd = 0.63).
3. The dashboard allows them to analyze data in ways they previously could not (mean = 3.82, sd = 0.51).
4. The data dashboard has made their work easier than it would be without the dashboard (mean = 3.89, sd = 0.38).
5. You have been appropriately trained to use the dashboard (mean = 3.26, sd = 0.87).
6. You prefer accessing data or reports yourself within the dashboard to asking for data or reports from

[5] We used the term "data dashboard" in many of our items, which we defined as "an integrated data system that can be accessed from the principals' desktop." In this district, I assume that principals will consider the Data Warehouse to be their system's data dashboard.

[6] Items with an asterisk (*) were reverse coded to provide an overall scale that measures principals' positive preferences and dispositions for using the system.

the central office (mean = 3.52, sd = 0.70).

7. You have not had time to learn how to use the data dashboard (mean = 1.68, sd = 1.00).*
8. The data dashboard does not provide you with anything you could not already obtain from the central office by asking for it (mean = 1.54, sd = 0.95).*
9. The data dashboard is more trouble than it is worth (mean = 1.22, sd = 0.75).*
10. The data dashboard provides you with useful data or reports (mean = 3.91, sd = 0.67).
11. You do not have time to use the dashboard (mean = 1.95, sd = 1.00).*
12. You prefer having someone else access the dashboard to prepare the reports you need rather than accessing the data yourself (mean = 2.04, sd = 0.91).*

These items address issues of both performance expectation (e.g., items 2, 3, 4, 5, 8, 9, 10) and ease of use (e.g., items 1, 6, 12), although I combine them into a single factor called the **Data Systems Scale** (alpha = 0.75). As the reported sample means for each of these items suggests, principals have favorable impressions of the ways in which the Data Warehouse makes work easier and provides them with information they could not access before, as well as positive impressions of its ease of use. The relatively small standard deviations also suggest that principals tend to agree on their opinions regarding the Data Warehouse.

Among the analytic sample of principals, their total use of the TVA website during the school year ranged from 0 to 63 times, with mean of 12.7 times and a standard deviation of 12.2.

Strategic Human Capital Decision Making

In the Conceptual Framework, I outline two general ways to explore whether principals may differ in their Data Warehouse use based on decisions regarding the use of data for human capital decision making. The first of these ways was to ask principals directly about their use of data for strategic human capital decision making in specific human capital areas (e.g., hiring, assignment, dismissal) and their perception of the barriers they face in using these data for these decisions. In the Principal Survey on Teacher Effectiveness Data Use for Human Capital Decision Making, we asked principals questions related to their use of teacher effectiveness data for hiring, assignment, and dismissal, as well as a question on their perception of barriers for using teacher effectiveness data for these decisions.

Hiring. To operationalize principals' self-reported use of teacher effectiveness data for hiring decisions, I use the following question: "Assume that you have the following data. How important were each of the following factors in making decisions about hiring teachers for your school?" Principals responded to this question with a 4-item Likert scale ranging from "Not a factor" to "A very important factor." The individual items were:

1. The teachers observation ratings (mean = 3.26, sd = 0.71).
2. A measure of the achievement growth of the teachers students in prior years (mean = 3.64 , sd = 0.65).
3. The teachers overall evaluation rating (i.e., a rating that combines observation ratings, growth measures, and other data into a single rating) (mean = 3.45 , sd = 0.64).
4. Direct observation of the teachers instruction in my school (e.g., in a demonstration lesson) (mean = 3.30 , sd = 0.96).

As the means and standard deviations of these items show, principals feel that these factors range from moderately important to very important. I also created a scale from these items which I called the **Hiring Scale** (alpha = 0.77).

Teacher Assignment. To operationalize principals' self-reported use of teacher effectiveness data for assignment decisions, I use the following question: "How much weight do you typically assign to each of the following factors in making decisions about which grade levels, classes of students, subjects, or courses a teacher will teach?" Principals responded to a 4-item Likert scale as with hiring, ranging from "Not a factor" to "A very important factor." The individual items were:

1. The teachers observation ratings (mean = 3.43, sd = 0.64).
2. A measure of the achievement growth of the teachers students in prior years (mean = 3.60, sd = 0.68).
3. Performance of the teachers students on benchmark assessments (mean = 3.49, sd = 0.64).
4. Performance of specific kinds of students in the teachers class on standardized tests (mean = 3.19, sd = 0.81).
5. The teachers overall evaluation rating (i.e., a rating that combines observation ratings, growth measures, and other data into a single rating) (mean = 3.26, sd = 0.69).

With regards to teacher assignment, it appears that principals rate the use of data as somewhere between an important and very important factor. I also create a scale from these items which I call the **Assignment Scale** (alpha = 0.84).

Teacher Dismissal. To operationalize principals' self-reported use of teacher effectiveness data for teacher dismissal decisions, I use the following question from the survey: "For a teacher for whom you made a decision/recommendation regarding the renewal of his/her contract last year, how important were each of the following factors?" Principals responded with the same scale as above, ranging from "Not a factor" to "A very important factor." The individual items were:

1. The teachers observation/appraisal ratings (mean = 3.57, sd = 0.65).
2. A measure of the achievement or growth of the teachers students (mean = 3.52, sd = 0.85).
3. The teachers overall evaluation rating (i.e., a rating that combines observation ratings, growth measures, and other data into a single rating) (mean = 3.57, sd = 0.72).

As with the other human capital decision areas, items related to teacher effectiveness data are also considered to be moderate to strong factors. I use these items to make a single scale which I call the **Dismissal Scale** (alpha = 0.80).

Barriers. As found in prior work on principals' use of teacher effectiveness data for human capital decision making, principals face a number of economic, contractual, cultural, and interpersonal barriers to data use for these decisions (Donaldson, 2013). With respect to Data Warehouse use, it may follow that principals who perceive greater obstacles to using the data for decision making may be less likely to use the Data Warehouse where the data are contained. To operationalize these barriers, I use the following question from the principal survey: "Below are potential barriers to using teacher effectiveness data (e.g., teacher observation data, student achievement growth data) for human capital decisions (e.g., teacher hiring, teacher renewal, teacher support, assignment of teachers to courses or grades). How much of a barrier does each one present for your use of teacher effectiveness data?" The principals then responded to a 4-item Likert scale ranging from "Not a barrier" to "A strong barrier." The items were:

1. Technology: Data are not accessible in an easy format (mean = 2.04, sd = 0.93).
2. Timing: Data are not available when decisions are made (mean = 3.07, sd = 0.96).
3. Skills and knowledge: You dont have enough understanding of the data or the skills to use the data (mean = 1.55, sd = 0.73).

4. District culture: The district does not expect data use (mean = 1.16, sd = 0.59).
5. Autonomy: You dont have autonomy over the decisions the data may inform (mean = 2.50, sd = 1.01).
6. Time: You dont have enough time or are too busy running your school (mean = 2.37, sd = 0.98).
7. Validity: Teachers do not believe the data are valid, legitimate, or useful for making human capital decisions (mean = 2.47, sd = 0.97).
8. Validity: You dont fully believe the data are valid, legitimate, or useful for making human capital decisions (mean = 1.73, sd = 0.89).
9. Lack of calibration: The calibration and consistency checks of the evaluation data (e.g., observations, teacher growth data) are not viewed as valid (mean = 1.97, sd = 0.90).
10. Teacher information: Teachers present evidence or information that contradicts the data (mean = 1.96, sd = 0.81).
11. Union rules: The teachers union does not support data use for decision-making (mean = 1.61, sd = 0.81).
12. Principal resistance: You are hesitant to engage personnel with difficult conversations (mean = 1.31, sd = 0.65).

In general, principals in this district do not perceive many barriers to data use for human capital decision making. The biggest barrier is the timing of when the data are made available, which I address in the next section. I combine these barriers into a single scale, which I call the **Barriers Scale** (alpha = 0.81).

The second way to examine principals' strategic human capital decision making is to examine their use of the Data Warehouse, particularly with respect to the types of reports they access and the timing of when they access them. Since the Data Warehouse contains over 200 reports, I decided to code each report into one of four mutually exclusive categories: (1) **student achievement report**; (2) **student demographic, behavior, and attendance report**; (3) **teacher report**, including information on teacher value-added or student achievement reports organized at the teacher level; and (4) **other report**. The total number of reports that were accessed by principals in the analytic sample in each category, as well as the number of principal Web logs for each category, are found in Table 3.

From this table, we learn that two-thirds of the reports focus on students, divided about evenly between reports that examine student achievement (e.g., benchmark scores, state standardized test scores) and reports that provide information on student demographic, behavior, and attendance (e.g., enrollment, absenteeism, discipline counts). We also learn that while there are a relatively small number of reports on teachers (11 reports, 7.9%), principal logins to the Data Warehouse to access these reports represents a little over 20% of all use.

Along with the types of reports principals' access, I will be able to use information on monthly Data Warehouse use to examine the alignment between principals' access of specific report types and the timing of various human capital decisions and data availability. This will help to provide a more complete picture of how different types of Data Warehouse users vary in their orientation towards strategic human capital decision making.

Table 3: Overview of Report Categories and Principal Web logs

	Report (Example)	Total # of Reports (%)	Principal Logins (%)
Student Achievement	Assessment Details For Active Students, DEA-TCAP Proficiency Trend, School Grades-Ach. Comparison, TCAP Three Year Comparison	48 (34.3%)	4,965 (37.2%)
Student Demographic, Behavior, & Attendance	Enrollment Counts, Mobility Rates and Distribution, Chronic Absence List, Daily Attendance Student List, Discipline Counts	47 (33.6%)	3,403 (25.5%)
Teacher Data	Teacher Attendance, Teacher Profile, TVAAS Projection	11 (7.9%)	2,921 (21.9%)
Other	Cluster Profile, Data Quality Details, Staff Job List	32 (22.9%)	2,068 (15.5%)
Total		**140**	**13,357**

Accountability

As described in the literature review and conceptual framework, school accountability pressures to improve performance or face high-stakes consequences like reconstitution seem to contribute to differences in data use (Fusarelli, 2008; Diamond and Cooper, 2007; Firestone and González, 2007). Yet "accountability" can relate not just to the pressures generated from educational policies (e.g., NCLB), but to the many formal and informal means of motivating and holding administrators responsible for their performance (Marsh, 2012). In this regard, central offices leaders and supervisors fill the role of encouraging principal data use, often through joint examination of student achievement data (Goertz et al., 2009) and/or by holding principals accountable for their human capital decision making (Cohen-Vogel, 2011; Grissom et al., 2014). To account for the more **formal** state accountability pressures schools may be under, I use information on student test score performance, specifically the percentage of students rated proficient or advanced on math and reading standardized tests, averaged over 3-years. For high schools, I use the average three year performance of students taking the ACT.[7] For principals in the analytic sample, the average 3 year percent proficient/advanced for math was 52.8% (s.d. = 8.80) and for reading was slightly lower at 49.7% (s.d. = 10.61). Average 3 year ACT scores for high school principals in the sample was 17.1 (s.d. = 1.53).

To account for the more informal accountability pressures principals may face, I use a single question from the principal survey which asks: "To what extent do the following statements describe your experiences with your home/central office regarding human capital decisions (e.g., teacher hiring, teacher renewal, teacher support, assignment of teachers to courses or grades) in the following ways?" This question contains 9 items, and principals were asked to respond to a 4-item Likert scale ranging from "Not at all" to "A large extent." The items were:

1. Asks you to justify decisions to hire particular teachers (mean = 1.94, sd = 0.84).
2. Monitors the completion rate of your teacher observations (mean = 3.16, sd = 0.77).
3. Ensures that the teacher observation ratings you assign to teachers are aligned with the evidence

[7] Note: All students in this state are required to take the ACT.

required in the observation rubric/framework (mean = 2.49, sd = 1.07).

4. Expects your teacher observation scores to align with student achievement measures (mean = 3.53, sd = 0.67).
5. Monitors the effectiveness of teachers you hired in the past (mean = 2.08, sd = 0.80).
6. Asks you to justify the assignment of teachers to particular subjects and classes (mean = 1.72, sd = 0.78).
7. Asks you to justify the decision to renew the contract of a particular teacher (mean = 1.59, sd = 0.74).
8. Produces reports that show how your teachers are changing in effectiveness over time (mean = 1.67, sd = 0.87).
9. Compares the professional development you provide to teachers to areas of need as demonstrated by teacher effectiveness data (mean = 1.91, sd = 0.92).

First, it is important to recognize that these items are oriented towards accountability for human capital decision making. As the means and standard deviations of these items suggest, this district seems to hold principals accountable for the teacher evaluation process and its results (i.e., completion rate, alignment of scores) but not their human capital decision making, with principals rating a majority of these items between "not at all" to "a small extent." Thus, while principals may face informal accountability pressures from the central office to improve performance or use data to drive improvement, it does not seem to come through the mechanism of their human capital decision making. This limitation in the measure notwithstanding, I have decided to combine these items into a single scale called **Central Office Accountability** (alpha = 0.82) and use it as a measure of informal accountability pressure.

As outlined in the conceptual framework, however, there are a number of other pressures principals may face to use data that I am not able to capture with these data. These include the pressure principals feel to monitor teacher performance on new teacher evaluation measures (i.e., value-added, teacher observation) and to maintain performance given a high amount of pressure from parents and communities.

School Context and Climate

Because school context may contribute to different data use practices and different information needs, I operationalize it using six measure:

- **School Level**, which I operationalize as elementary (54.9 %) or middle/high (45.1%)
- **Enrollment** (median = 526 students, s.d. = 365.0)
- **Percent of Students on Free-Reduced Price Lunch (FRPL)** (mean = 74.8%, s.d. = 23.4)
- **Percent of Students who are English Learner (EL)** (mean = 13.3%, s.d. = 17.7)
- **Percent of Students who are Special Education (SPED)** (mean = 12.3%, s.d. = 10.2).

To account for student racial/ethnic diversity within schools, I use a measure of racial/ethnic entropy, which captures the extent to which the school is racially/ethnically isolated (Iceland, 2004; Reardon et al., 2000). More specifically, the entropy index measures the spatial distribution of multiple racial/ethnic groups in the school (i) according to the following equation:

$$Entropy_i = -\sum_{j=1}^{k} p_{ij} \ln(p_{ij}) \tag{III.1}$$

where

k = the number of racial/ethnic groups ($k = 4$; White, African American, Hispanic, Asian);

p_{ij} = the proportion of the students of jth race/ethnicity in school i;

n_{ij} = the number of population of jth race/ethnicity in school i; and

n_i = the total number of students in school i.

The maximum value of $Entropy_i$ is $\ln(k)$ or $\ln(4) = 1.39$. Thus, a school with an entropy index of 1.39 would have equal proportions of all racial/ethnic groups (i.e., maximum diversity) and a school with an entropy index of 0 would contain only one ethnically homogenous group. In my analytic sample, school entropy measures range from 0.04 to

1.27, with an average index of 0.93.

Along with these school compositional and student demographic measures, I use information on teacher reports of school climate from the TELL survey to capture heterogeneity in principals' job conditions. Items on the TELL survey ask teachers to rate their level of agreement (i.e., strongly disagree, disagree, agree, strongly agree) with statements regarding their schools' culture and environment. I have chosen to use items that capture the condition of the school's facilities, the community support, and student behavior, with the idea that variation in each of these conditions may contribute to the amount of time a principal has to use the Data Warehouse. The questions and items are as follows:

School Facilities. Teachers were asked: "Please rate how strongly you agree or disagree with the following statements about your school facilities and resources." Publicly available data provides information on the proportion of teachers who agree or strongly agreed to the following items:

1. Teachers have sufficient access to appropriate instructional materials (mean = 0.82%, sd =0.12).
2. Teachers have sufficient access to instructional technology, including computers, printers, software and internet access (mean = 0.76%, sd =0.17).
3. Teachers have access to reliable communications technology, including phones, faxes and email (mean = 0.92%, sd =0.07).
4. Teachers have sufficient access to office equipment and supplies such as copy machines, paper, pens, etc (mean = 0.76, sd =0.17).
5. Teachers have sufficient access to a broad range of professional support personnel (mean = 0.81, sd =0.12).
6. The school environment is clean and well maintained (mean = 0.78, sd =0.18).
7. Teachers have adequate space to work productively (mean = 0.89, sd =0.09).
8. The physical environment of classrooms in this school supports teaching and learning (mean = 0.87, sd =0.12).
9. The reliability and speed of Internet connections in this school are sufficient to support instructional practices (mean = 0.77, sd =0.14).

As the results from these items suggest, teachers in principals' schools in the analytic sample have generally consistent and positive feelings about the conditions of the facilities, with very little variation. I combine these items into a single scale called **Facilities Scale** (alpha = 0.90).

Community Support. Teachers were asked the following regarding community support: 'Please rate how strongly you agree or disagree with the following statements about community support and involvement in your school." The data for each item was reported as the proportion of teachers who agreed or strongly agreed with the following:

1. Parents/guardians are influential decision makers in this school (mean = 0.60, sd =0.24).
2. This school maintains clear, two-way communication with parents/guardians and the community (mean = 0.85, sd =0.13).
3. This school does a good job of encouraging parent/guardian involvement (mean = 0.87, sd =0.13).
4. Teachers provide parents/guardians with useful information about student learning (mean = 0.93, sd =0.06).
5. Parents/guardians know what is going on in this school (mean = 0.82, sd =0.16).
6. Parents/guardians support teachers, contributing to their success with students (mean = 0.67, sd =0.21).
7. Community members support teachers, contributing to their success with student (mean = 0.81, sd =0.14).
8. The community we serve is supportive of this school (mean = 0.81, sd =0.16).

Here we also find that teachers have generally positive views about community support and engagement, with little variability. I combine these items into a single scale call **Community Support Scale** (alpha = 0.93).

Managing Student Conduct. Teachers were asked the following with respect to student conduct: "Please rate how strongly you agree or disagree with the following statements about managing student conduct in your school." As with the other items in TELL, the publicly available data reported the proportion of teachers that agreed or strongly agreed with the following:

1. Students at this school understand expectations for their conduct (mean = 0.83, sd = 0.15).
2. Students at this school follow rules of conduct (mean = 0.67, sd = 0.26).
3. Policies and procedures about student conduct are clearly understood by the faculty (mean = 0.82, sd = 0.14).
4. School administrators consistently enforce rules for student conduct (mean = 0.70, sd = 0.21).

5. School administrators support teachers' efforts to maintain discipline in the classroom (mean = 0.78, sd = 0.18).
6. Teachers consistently enforce rules for student conduct (mean = 0.79, sd = 0.15).
7. The faculty work in a school environment that is safe (mean = 0.89, sd = 0.14).

As with the other questions from TELL, there is not a lot of variation in these items and teachers have positive views about student conduct. I combine these items to create a single scale **Student Conduct Scale** (alpha = 0.95).

CHAPTER IV

ANALYTIC STRATEGY

IV.1 Overview of Analytic Strategy

Researchers often employ statistical analyses like regression, factor analysis, and structural equation modeling to take a variable-centered approach to data analysis (Muthén and Muthén, 2000). Such analyses often focus on the relationships among **variables**, including the prediction of outcomes; the relationships between constructs and indicators; and the structural relationship(s) between independent and dependent variables. For example, in this dissertation I might use regression analysis to examine the relationship between the measures outlined above and principals' Data Warehouse use. I might further use the longitudinal nature of the data to examine whether time plays an influence on principals' use.

In contrast, cluster analysis, finite mixture analysis, latent class analysis, and latent transition analysis take a person-centered approach to data analysis, where the goal is to focus on the relationship among **individuals** (Muthén and Muthén, 2000). In these studies, researchers often wish to model some phenomena based on distinct sub-groups, types, or categories of individuals (**?**). While conventional approaches often assume that individuals come from a single population with a single latent development or growth trajectory (Raudenbush and Bryk, 2002), latent class- or growth-mixture models offer researchers the opportunity to examine inter-individual differences in intra-individual change **while** taking into account unobserved heterogeneity within the larger population (Jung and Wickrama, 2008). For example, research on alcohol consumption (Muthén and Muthén, 2000; Bucholz et al., 1996) and crime (Nagin and Tremblay, 1999; Broidy et al., 2003) have been able to document the existence of distinct developmental classes in the population, in accordance with previous theory.

Accordingly, in this dissertation I use latent class growth analysis (LCGA) to examine the growth trajectories of principals' data systems use over the course of the 2013-2014 school year. LCGA is particularly well suited to the present study because of its ability to (1) account for heterogenous sub-populations of technology users, like those that may be found among the US adults population (Horrigan, 2007); (2) fully utilize the longitudinal nature of the data; and (3) examine the influence of important covariates on class membership.

IV.1.1 Motivation for Latent Class Growth Modeling

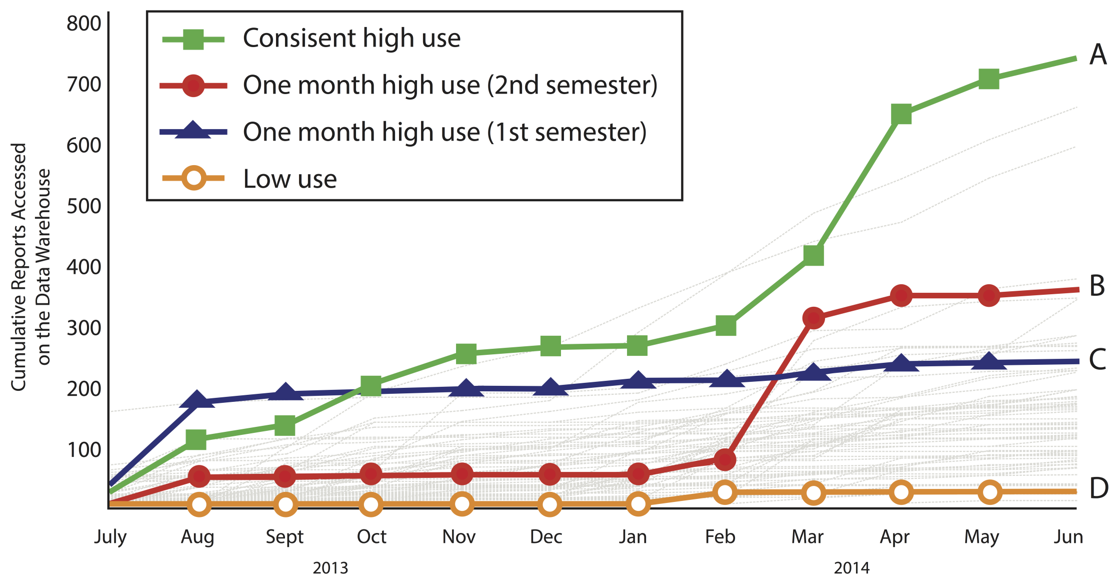

Figure 4: Trajectories of Principals' Cumulative Use of the Data Warehouse, 2013-2014

LCGM assumes that the observed means, variances, and covariances of principals' Data Warehouse use over the course of the school year were generated by a continuous process of principal data systems' use. Figure 4 show each principals' trajectory of cumulative use during the 2013-2014 school year. I have highlighted four individual principals to demonstrate different patterns of use. Principal A's trajectory shows consistent, high use of the Data Warehouse. Principals B and C both have a single month of very high use in March and August, respectively, but relatively little use of the system during the other 11 months. Principal D appears to be among a large group with little use of the system throughout the entire school year. Importantly, Figure 4 demonstrates that we should not assume that the continuous developmental process of Data Warehouse use is monotonic for all principals. Rather, I argue that this unobserved heterogeneity arises from the mixing of homogenous subpopulations of technology users, as highlighted in the Pew Internet and American Life Project Survey and as described in Section II.2 (Horrigan, 2007).

IV.1.2 Assumptions, Model Specification, Estimation, and Fit

There are a few key assumptions with LCGM. First, as mentioned above, each type or class of principal Data Warehouse user contains separate growth models, each with its own unique estimates of variances and covariance influences (Jung and Wickrama, 2008). Although the residual variances of the dependent variables may differ across user type, I have decided to fix these as class invariant (Nagin, 2005).[1] In addition, I make the assumption that, after accounting for class membership, individual principals **within** a class differ only due to random error (i.e., individuals are interchangeable). Thus, the covariances among the dependent variables in the sample are due solely to between class differences in the class parameters.

Since the data are longitudinal, the within-class means are structured to follow a time trend. A linear time trend, for instance, would be estimated using the following equation:

$$y_{ij} = \eta_0^{(k)} + \eta_1^{(k)} time_{ij} + \varepsilon_{ij} \qquad \varepsilon_{ij} \sim N(0, \sigma_j^{2(k)}) \qquad \text{(IV.1)}$$

where,

y_{ij} = cumulative Data Warehouse use for principal i at month j,

$time_{ij}$ = time score (e.g., 0 to 11) for principal i at month j,

[1] This technique is both common in the literature (Berlin et al., 2014; Nagin and Tremblay, 1999) and allows for faster model convergence (Kreuter et al., 2007; Jung and Wickrama, 2008).

$\eta_0^{(k)}$ = class-specific intercept; model-implied mean when $time = 0$,

$\eta_1^{(k)}$ = class-specific linear slope;

ε_{ij} = person i's deviation from their class trajectory, at month j, and

$\sigma_j^{2(k)}$ = within-class residual variance at month j, fixed across class and time.

Importantly, LCGA allows for non-linear class-specific trajectories, which are estimated using higher-order polynomials (i.e., quadratic, cubic).

Model parameters are estimated using the robust maximum likelihood estimator (MLR; Mplus v.7). Since the iterative computation of maximum likelihood estimates (i.e., the EM algorithm) may converge on a local maximum instead of the true global ML estimates (Dempster et al., 1977), for each model I run at least 1000 sets with random starting values to generate the parameter estimates and then iterate using the 100 best possibilities until model convergence.

In order to decide on the number of latent classes k, I use three considerations, as recommended by Muthén and Muthén (2000). First, I use an exploratory, sequential approach to select the optimal number of classes, according to the Bayesian information criterion (BIC), which is designed to maximize the likelihood and keep the model parsimonious (Nagin and Tremblay, 1999; Nagin, 2005). Specifically, I will fit 2-, 3-, and 4-class models with linear and higher-order polynomial (i.e., quadratic, cubic) time trends.

Second, for each principal, I examine the average posterior probability for each class to make sure that the highest probability is considerably higher than the average posterior probability for other classes for that individual. Ideally, each principal will have a posterior probability close to 1 for a particular latent class, and nearly 0 for all the other latent classes. Individuals in this group will have very little error associated with their assigned latent class. However, it is often the case that individuals within a sample may have a response pattern than produces a high degree of uncertainty associated with their assigned latent class. Accordingly, I will also examine the mean posterior probability for each latent class and the variation about the mean (**?**) as well as an entropy-based measure of uncertainty, or the weighted average of individuals' posterior probabilities (Ramaswamy et al., 1993). In doing so, I will be able to determine the extent to which individual principals' class assignments are associated with a single type of Data Warehouse use.

Finally, I examine the usefulness of latent classes in the context of the study. Specifically, I will examine the trajectory shapes for similarity, the number of individuals in each class, and the number of estimated parameters. Given the small sample size and large number of covariates used in this study, I will be especially sensitive to latent class size and trajectory shape, with preference given to larger class sizes and more distinct types of Data Warehouse use.

IV.1.3 Predicting Differences in Data Warehouse User Types

Research Questions 2 through 4 explore the relationship between principals' predicted type of Data Warehouse use and factors related to technology, technology use, strategic human capital decision making, school accountability, and school context. To examine these relationships, I use a two-step "classify-analyze" approach (Clogg, 1995), where I first fit an unconditional LCGA model to estimate each principal's most-likely class membership or type of Data Warehouse use. I will then treat each principal's predicted class membership as observed and examine covariate influences using logistic and multinomial logistic regression.[2]

[2] It should be noted that this approach is technically inappropriate, in that conventional statistical methods, such as logistic and multinomial logistic regression, assume that there is no classification error. However, in these analyses principals' class assignments are probabilistic, not certain (Nagin, 2005). Nontheless, simulation studies suggest that when entropy is high (i.e., greater than 0.80), most likely class membership was among the best performing methods in terms of recovering the true value (Clark, 2010).

CHAPTER V

RESULTS

V.1 RQ1. Are there significantly different types of Data Warehouse users among principals?

In order to determine if there are different types of Data Warehouse users among principals, I fit a series of LCGA models that varied by the number of "classes," or number of Data Warehouse user types, as well as by the functional form (i.e., linear, quadratic, cubic) each class may take. As outlined in the conceptual framework, principals' have their own personal inclinations, dispositions, skills, and preferences towards technology and technology use. As reported in the Pew Internet and American Life Survey, U.S. adults generally fall into one of three broad groups of technology users: **Elite Tech Users**, or principals for whom the process of logging on and navigating within the Data Warehouse will be second nature; **Middle-of-the-Road Tech Users**, or principals who may find the Data Warehouse useful in helping them do their job, but also may consider the process of using the system to be quite burdensome; and **Users with Few Tech Assets**, or principals who prefer old modes of work and find the Data Warehouse to be largely unnecessary.

As I result, I begin by fitting a 3-class model, then I fit a series of 2- and 4-class models to compare which of these fit the data the best. To determine the best fitting model, I use a combination of model fit indices (the BIC and AIC) and the models' ability to distinguish between user types (entropy). Table 4 I summarize the results.

The 3-class models are consistent across most-likely class membership; that is, principals are identified with the same Data Warehouse user type regardless of functional form specification. Importantly, model estimates were replicated, suggesting a global solution and increasing the stability of the findings. In addition, the entropy for each these models is very close to 1 and the average latent class probabilities for most likely latent class membership by latent class are 1.00, 1.00, and 0.995 respectively. Thus, each of the 3-class models, regardless of functional form specification, are able to accurately distinguish between Data Warehouse user types.

The 2-class models show that the number of principals who are most likely associated with a given Data Warehouse user type varies in terms of different functional form specifications. A visual plot of these different 2-class models (not shown here) shows that the linear and quadratic specifications fit two user types—one group with little to no use (Class 1), and another with a constant rate of use (i.e., the linear specification) or an increasing trend in use (i.e., the quadratic specification) over the course of the school year (Class 2). Furthermore the quadratic specification fits the data the best according to the AIC and BIC. The cubic specification, while it does not fit the data the best according to these model fit indices, does show a second class of 7 principals with a cubic trajectory in Data Warehouse use. The value of the entropy (1.00) suggests a high degree of accuracy in distinguishing these two user types. In comparison to the 3-class model, however, the BIC and AIC suggest that these specifications do not fit the data as well.

While the 4-class model fits the best according to the BIC, the small number of principals in classes 1 and 4 across all three functional form specifications and a visual inspection of the average monthly use (not shown here) suggests that classes 2 and 3 follow roughly parallel trajectories, making interpretability difficult (Muthén and Muthén, 2000). In addition, the best likelihood value of the cubic model was not replicated, suggesting that the solution may not be trustworthy due to local maxima.

As a result, I find that as the Pew Internet and American Life Survey suggests, principals form three significantly different and distinct types of Data Warehouse users. Figure 5 provides a visual illustration of each of these groups. To fit this model, I used a visual inspection of the estimated means to fit a quadratic function for class 1, a linear function for class 2, and a cubic function for class 3. Table 5 summarizes the results. I

Table 4: Summary of Model Fit, by Number of Latent Classes and Functional Form Specification

2-Class			
	Linear	*Quad*	*Cubic*
AIC	10084.286	10067.375	10846.398
BIC	10122.793	10108.289	10889.719
N (Class 1)	48	47	75
N (Class 2)	34	35	7
Entropy	0.813	0.824	1.00
3-Class			
	Linear	*Quad*	*Cubic*
AIC	10056.350	10038.220	10034.999
BIC	10104.485	10093.575	10097.574
N (Class 1)	43	43	43
N (Class 2)	32	32	32
N (Class 3)	7	7	7
Entropy	0.995	0.995	0.995
4-Class			
	Linear	*Quad*	*Cubic**
AIC	9006.895	9989.261	8919.737
BIC	9055.281	10047.022	8984.251
N (Class 1)	3	6	2
N (Class 2)	31	28	26
N (Class 3)	31	36	39
N (Class 4)	9	12	7
Entropy	0.979	0.965	0.974

*The best loglikelihood value was not replicated.
The solution may not be trustworthy due to local maxima

Table 5: Class specific estimates

	Intercept	Linear Slope	Quadratic Slope	Cubic Slope
Low Use	7.172***	0.591	0.720*	-
	(1.148)	(1.255)	(0.310)	
Middle-of-the-Road	21.290***	17.456***	-	-
	(3.687)	(3.193)		
High Flyers	85.772***	42.322**	-3.953	0.366*
	(23.838)	(15.076)	(3.306)	(0.167)

Author's calculations. n = 82; standard errors in parentheses.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

now briefly describe each Data Warehouse user type.

Class 1: Low Use

The first class contained a little over half of the principals in the sample (n = 43, 52.2%). Individuals in this group used the Data Warehouse an average of about 7 times in July (unstandardized mean = 7.172) with a rate of change of less than 1 (unstandardized linear slope = 0.591), although there appears to be a slightly increasing trend in use over the course of the school year (unstandardized quadratic slope = 0.720, $p<0.05$). As a result, these estimates suggest that principals in this group use the Data Warehouse a **total** of about 22 times during the school year. I have labelled this group "Low Use."

Class 2: Middle-of-the-Road Users

The second class contains roughly 40% of principals in the sample (n=32, 39.3%). Principals in this group used the Data Warehouse an average of about 21 times in July, and for each passing month used the Warehouse an additional 17 times (unstandardized mean slope = 17.456, $p<0.001$). Thus, by the end of the year principals in this group used the system a total of about 215 times. I have labelled this group "Middle-of-the-Road Users."

Class 3: High Flyers

The third and final class contains a small percentage of principals in the sample (n=7, 8.5%). Principals in this group averaged about 86 uses of the Data Warehouse in July, and each month used the system an additional 42 times, with less use in the winter months and more use in the latter part of the year (i.e., the cubic trend). In total, principals in this group use the Data Warehouse about 511 times during the school year. I have labelled this group the "High-Flyers."

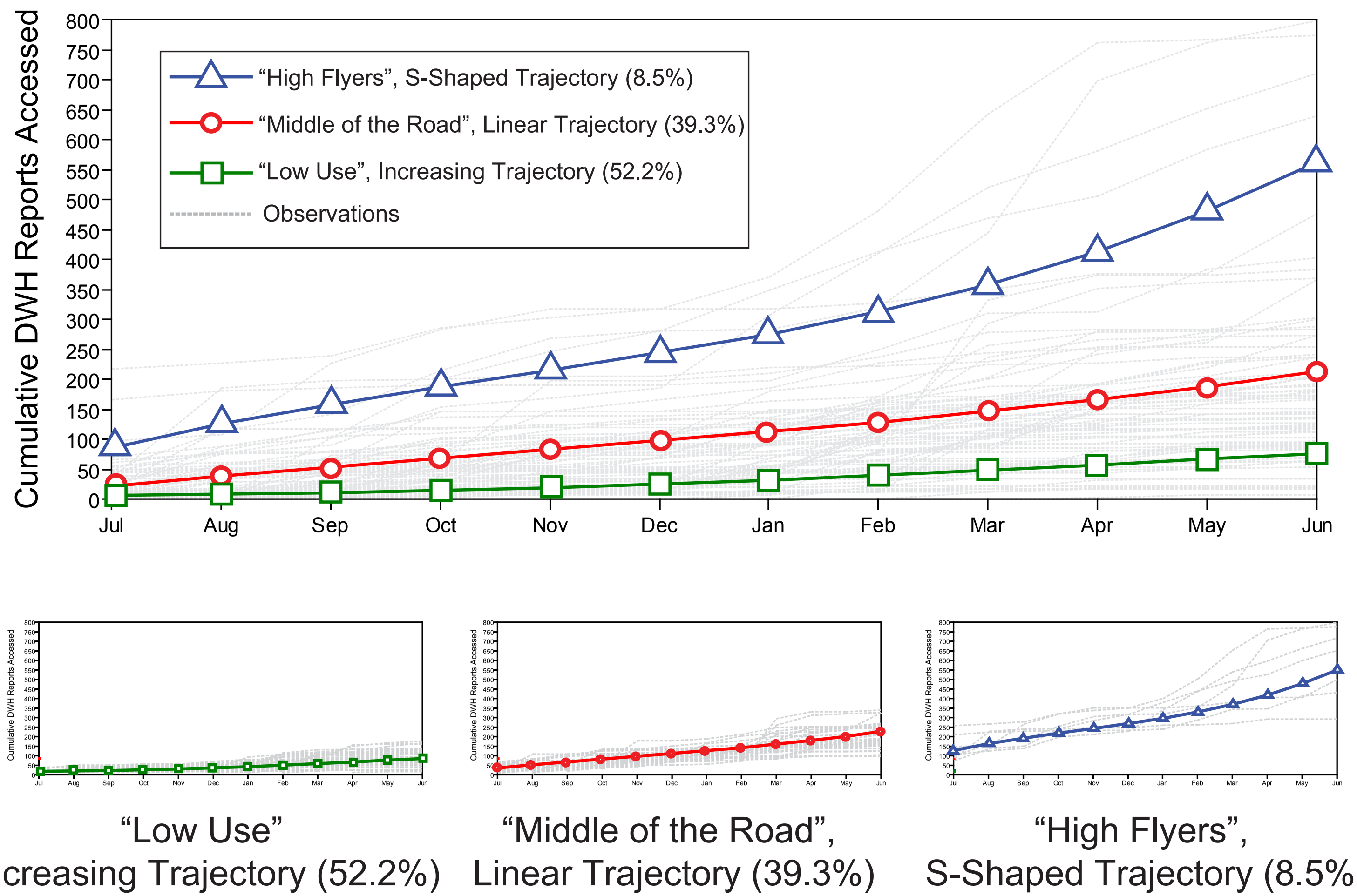

Figure 5: Estimated 3-Class Model, with Observed Values

V.2 Exploring Differences in Types of Data Warehouse Users

In order to examine the extent to which differences in these three distinct types of Data Warehouse users can be explained by technology and technology use (RQ2), strategic behavior by principals to use data for human capital decision making (RQ3), and principal responses to their environmental context and climate (RQ4), I will use a series of limited dependent variable models (LDV). Because I have a limited sample size more generally (n=82) and specifically with respect to the High Flyer class (n=7), I will fit either a multinomial logit model or a logit model. More specifically, for those models that with a small number of covariates, I estimate a multinomial logistic model predicting class membership, using the Low Use trajectory class as the reference category. Using maximum likelihood estimation, I estimate the following:

$$\pi_j(X_i) = \frac{e^{X_i\theta_j}}{\sum\limits_j e^{X_i\theta_j}} \tag{V.1}$$

where,

$\pi_j(X_i)$ = the probability of membership in group j given X_i,

X_i = a set of explanatory variables, and

θ_j = captures the impact of the covariates of interest X_i on the probability of group membership.

To interpret these estimates, I will report the relative risk ratios (RRR) that indicate the relative odds that principals will be in a Middle-of-the-Road or High Flyer class as opposed to the Low User class.

For those models with a greater number of covariates, I combine principals from the Middle-of-the-Road and High Flyer classes and estimate a logit model, with Low Use as the reference category. Specifically, I use maximum likelihood estimation to estimate the following:

$$\pi_1(X_i) = \frac{e^{\beta_0 + X_i\beta}}{1 + e^{\beta_0 + X_i\beta}} \tag{V.2}$$

where,

$\pi_1(X_i)$ = the probability of membership in the Middle-of-the-Road and High-Flyer classes given X_i,

X_i = a vector of explanatory variables, and

β = the corresponding vector of coefficients.

To interpret these estimates, I will report the odds ratios (OR), which indicate the change in odds of being in the Middle-of-the-Road and High Flyer classes given changes in the covariates of interest.

V.2.1 RQ2. How do principals' personal inclinations to use technology and/or their views of the Data Warehouse distinguish types of Data Warehouse users?

The research literature on information systems' use in organizational settings suggests that individuals' own dispositions to use technology will influence the way in which they interact with computer systems (Davis, 1989; Venkatesh et al., 2003). As outlined in the conceptual framework, these dispositional differences may be due to variation in principals' ages, gender, expected performance of the Data Warehouse, and perceived ease of use.

In Table 6, I calculate the means and standard deviations of each of these variables by Data Warehouse user type. These descriptive results show few substantive differences between the Low Use and Middle-of-the-Road user types, except that there are a smaller proportion of females in the middle-class and they tend to use the TVA website on average about 6 times more than the low use class during the school year. Their years' experience and their perceptions of the Data Warehouse's expected performance and ease of use are nearly identical, although a few survey items suggest that they have opinions of the system

Table 6: Technology and Technology Use, by Type of Data Warehouse User

	Low Users		Middle Users		High Flyers	
Female	0.65	.	0.53	.	0.71	.
Years' Experience	8.36	(6.46)	8.04	(6.34)	3.86	(4.30)
Data Systems Scale (standardized)	−0.04	(0.38)	−0.08	(0.70)	0.01	(0.22)
DWH easy to navigate*	3.49	(0.61)	3.33	(0.83)	3.43	(0.53)
DWH allows access to new data*	3.66	(0.59)	3.67	(0.83)	3.86	(0.38)
DWH allows new analysis*	3.63	(0.65)	3.77	(0.59)	4.00	(0.00)
DWH makes work easier than before*	3.80	(0.41)	3.89	(0.42)	3.86	(0.38)
Appropriate training*	3.23	(0.88)	3.07	(1.00)	3.57	(0.53)
Prefer to use DWH to access data reports*	3.26	(0.78)	3.44	(0.75)	3.57	(0.79)
No time to learn to use DWH*	1.71	(0.84)	1.65	(1.09)	1.43	(0.79)
DWH provides nothing new*	1.97	(1.29)	1.59	(0.97)	1.29	(0.49)
DWH more trouble than it's worth*	1.26	(0.66)	1.26	(0.86)	1.00	(0.00)
DWH provides useful data reports*	3.89	(0.68)	3.78	(0.85)	4.00	(0.00)
No time to use the DWH*	1.79	(0.88)	1.74	(1.02)	2.29	(0.95)
Prefer to have others use DWH*	2.29	(0.86)	2.00	(0.96)	2.00	(0.82)
TVA Use	8.47	(7.24)	14.38	(12.12)	32.00	(17.72)
Observations	34		27		7	

Note: Authors calculations. Standard deviation in parentheses. "DWH" = Data Warehouse
*Items based off a Likert Scale: 1 = "Disagree strongly"; 2 = "Disagree"; 3 = "Agree"; 4 = "Agree strongly"

that align with their different Data Warehouse use patterns. Examples include differences in their level of disagreement with the statements, "the Data Warehouse provides nothing new," and "You prefer to have others use the Data Warehouse," with Middle-of-the-Road users expressing stronger disagreement.

Differences between both the low- and middle-use classes and the High Flyers are most noticeable with respect to their years' experience as a principal and their use of the TVA website. More specifically, principals in the High Flyers have an average of about 5 years less experience, and they use the TVA website about 4 times as much as the Low Users and over 2 times as much as the Middle-of-the-Road users.

In order to examine whether these results are statistically significant, I ran a multinomial logit model. These results are reported in Table 15. With respect to principal years' experience, these results suggest that each additional year of experience is associated with a 23% reduction in the odds of being in the High Flyer class versus Low Use class (RRR = 0.77, p = 0.03), given that the other variables in the model are held constant. With respect to TVA use, each additional time a principal logs in is associated with a 7% increase in the odds of being in the Middle-of-the-Road user class (RRR = 1.07, p = 0.04) versus the Low Use class, and a 29% increase in the odds of being in the High Flyers versus the Low Use class (RRR = 1.29, p = 0.001), ceteris paribus. As evident from the descriptive table, the differences in views of the Data Warehouse do not appear to be associated with differences in Data Warehouse user type, a finding that seems to be associated with the generally positive attitudes principals have towards the system, its ease of use, and the ways in which it can improve their work.

More generally, these results suggest that principals' Data Warehouse use may be more a product of their preferences for using technology more generally and not necessarily the Warehouse itself. That is, principals who are younger (i.e., in terms of experience and/or age) seem more pre-disposed to using technology in **any** of its forms, with the association between TVA use and Data Warehouse user type presenting strong empirical evidence in favor of this hypothesis.

Nonetheless, this finding alone seems too technologically deterministic and does not allow for differences in principals' preferences for using data strategically and/or in response to their environmental context. I explore these hypotheses in the next two sections.

Table 7: Multinomial Logit Results for Measures Associated with Technology and Technology Use (DV = Predicted Class)

	Latent Class			
	Middle-of-the-Road		**High Flyers**	
	RRR	95% C.I.	RRR	95% C.I.
Years' Experience	0.97	(0.89, 1.05)	0.77*	(0.61, 0.98)
Data System (Scale)	0.64	(0.22, 1.82)	0.13	(0.00, 12.37)
TVA Use	1.07*	(1.00, 1.14)	1.29**	(1.11, 1.50)
N	69			

Reference Category = "Low Use"
+ p<.10, * p<.05, ** p<.01

V.2.2 RQ3. How does principals' orientations towards data use for strategic human capital decision making distinguish types of Data Warehouse users?

An increasingly important part of the data use in education narrative is a vein of research that explores how schools leaders use data to inform not their instructional, but human capital decision making (Goldring et al., 2015; Cohen-Vogel, 2011; Cannata et al., 2014; Drake et al., 2014a). The Data Warehouse offers principals oriented towards data use for human capital decision making an incredible resource for principals in that it provides them with a host of organized data reports on their students and teachers—reports that are updated as soon as new data become available and can be uploaded to the server. Thus, differences in principals Data Warehouse use may be associated with their differences in their data use for strategic human capital decision making.

In the conceptual framework I outline two ways to examine this hypothesis: first, I use results from a survey of principals in the district to explore differences in their responses to questions regarding their data use for teacher hiring, assignment, and dismissal decisions, by Data Warehouse user type. I also examine differences in principals' views on various barriers for teacher effectiveness data use for human capital decision making.

Using this method, I might expect to find that principals in the Middle-of-the-Road and High Flyer classes report that they assign greater weight to the use of teacher effectiveness measures for these decisions. In Table 8, I find some evidence to suggest that this is the case with respect to hiring and dismissal decisions, though overall differences between groups are small and variation within groups is relatively large. More specifically, principals in the Middle-of-the-Road and High Flyer classes seem to assign greater weight to measures such as student achievement and growth data and overall evaluation scores—data that are easily accessible in the Data Warehouse. The degree to which principals consider teacher observation data also seems to vary by user type, with the High Flyers reporting the highest average responses, though it should be noted that these data are not available in the Data Warehouse. Weight in teacher assignment decision

Table 8: Survey Items on HC Decision Making, by Type of Data Warehouse User

	Low Users		Middle Users		High Flyers	
Teacher Hiring Scale (Standardized)	-0.06	(0.95)	-0.03	(0.62)	0.19	(0.41)
Hiring: Use of observation data*	3.29	(0.84)	3.22	(0.75)	3.50	(0.55)
Hiring: Use of student achv./growth data*	3.44	(0.86)	3.63	(0.69)	3.67	(0.52)
Hiring: Use of overall evaluation score*	3.24	(0.83)	3.52	(0.64)	3.50	(0.55)
Hiring: Direct observation of instruction*	3.06	(1.12)	3.33	(1.07)	3.50	(0.55)
Teacher Assignment Scale (Standardized)	-0.11	(0.75)	0.09	(0.42)	-0.01	(0.54)
Weight in Assign: Observation Scores*	3.21	(0.88)	3.48	(0.64)	3.43	(0.53)
Weight in Assign: Acv/Growth*	3.21	(0.98)	3.63	(0.63)	3.86	(0.38)
Weight in Assign: Student benchmark scores*	3.32	(0.88)	3.44	(0.64)	3.71	(0.49)
Weight in Assign: Subgroup performance*	3.15	(0.89)	3.30	(0.82)	3.14	(0.90)
Weight in Assign: Overall evaluation score*	3.18	(0.90)	3.37	(0.63)	3.14	(0.69)
Teacher Dismissal Scale (Standardized)	-0.13	(1.08)	-0.01	(0.72)	0.21	(0.39)
Dismissal: Importance of observation scores*	3.48	(0.87)	3.54	(0.65)	3.71	(0.49)
Dismissal: Importance of achv/growth*	3.53	(0.98)	3.62	(0.80)	3.50	(0.84)
Dismissal: Importance of overall evaluation*	3.44	(0.91)	3.58	(0.76)	3.71	(0.49)
Barriers Scale (Standardized)	-0.12	(0.61)	0.12	(0.61)	0.03	(0.43)
Technology: Data not in accessible format**	1.71	(0.89)	2.15	(1.06)	2.29	(0.76)
Timing: Data not available for decision-making**	2.68	(1.04)	3.19	(0.83)	3.14	(1.07)
Principal lacks skills/knowledge**	1.80	(0.76)	1.81	(0.80)	1.14	(0.38)
District culture**	1.18	(0.53)	1.33	(0.88)	1.00	(0.00)
Lack of autonomy**	2.17	(1.10)	2.44	(1.19)	2.86	(0.69)
No time**	2.12	(0.95)	2.48	(0.94)	2.57	(1.13)
Teacher don't believe data are valid**	2.40	(0.95)	2.56	(1.01)	2.29	(0.95)
Principals don't believe data are valid**	1.70	(0.85)	1.81	(1.00)	1.71	(0.95)
Lack of calibration**	1.82	(0.83)	2.04	(0.98)	2.29	(1.11)
Conflicting information from teachers**	1.82	(0.87)	2.15	(0.82)	1.86	(0.90)
Union does not support**	1.56	(0.82)	1.78	(0.89)	1.50	(0.84)
Principal hesitant to have difficult discussions**	1.27	(0.57)	1.41	(0.80)	1.43	(0.79)
Observations	34		27		7	

Note: Authors calculations. Standard deviation in parentheses.

*Items based off a Likert Scale: 1="Not a factor"; 2="Minor factor"; 3="Moderately important factor"; 4="Major factor"

**Items based off a Likert Scale: 1="Not a barrier"; 2="Minor barrier"; 3="Moderate barrier"; 4="Strong barrier" does not seem to vary by Data Warehouse user type, a finding that seems to be consistent across many districts engaged in the work of teacher evaluation and data use (Goldring et al., 2015).

Table 8 also reports differences in principals' responses to a question regarding their perceptions of various barriers to data use for human capital decision making. Here I might expect to find that principals for whom these barriers are not strong are those who access these data more through the Data Warehouse. Nonetheless, I find that the opposite seems to be true—principals in the Middle-of-the-Road and High Flyer class perceive these barriers to be stronger than principals in the Low use class, a finding that seems to be supported by the logit results (Table 9).

To further explore this finding, Table 8 suggests that these differences are mainly driven by differences in the perceived barriers of technology (i.e., data are not in an accessible format); timing (i.e., data are not available for decision making); lack of autonomy; and lack of time to use the data. In thinking about each one of these individual items, it may be that those principals who are **most** oriented towards data use for strategic human capital decision making would find these to be the biggest barriers in that they are most familiar with them. With respect to use of the Data Warehouse itself, the technology barrier is an interesting one to consider, in that principals who are most familiar with the data reports may be among those who are most likely to find that their format are not conducive to decision making.[1] It should be noted, however, that averages across all these items are relatively low, somewhere between "not a barrier" and a "small" or "moderate barrier."

In general, there does not seem to be strong evidence to support the association between strategic human capital decision making and type of Data Warehouse user from this survey. Nevertheless, these items come from principals' self-reported behaviors from

[1] Future work with the district suggests that this may be the case, in that we have been working with the district to reformat the way in which the data are presented so as to provide principals with data organized around human capital decision areas.

Table 9: Logit Results for Measures Associated with Human Capital Decision Making (DV = Predicted Class)

	Middle-of-the-Road / High Flyers
	OR
Hiring Scale	1.21
	(0.41,3.53)
Assignment Scale	2.58
	(0.64,10.42)
Dismissal Scale	0.87
	(0.31, 2.44)
Barriers Scale	2.92+
	(1.06, 8.07)
N	65

Exponentiated coefficients; 95% confidence interval in parentheses
Reference group: Low Use
+ p<.10, * p<.05, ** p<.01

a survey. As a result, I also examine **what types of data** principals access on the Data Warehouse and **when** they access them, by user class, in order to examine not self-reported, but actual data use. Specifically, I examine when and how often principals in each of the three Data Warehouse user types access data reports containing information on (1) student achievement, (2) student demographics, behavior, and attendance, and (3) teacher data, including teacher value-added and student achievement information organized by teacher.

Figure 6 reports the average cumulative monthly use, by each of these data report types and predicted class, over the school year. In interpreting these figures, it may be helpful to look for any patterns that may emerge. In particular, the timeline of data availability and human capital decision windows (Figure 1) suggests that principals may access data more when they become available and/or when important human capital decisions need to be made, the majority of which occur during the spring semester.

To explore for these patterns, it may be helpful to first look within class across data report type. The Low Use class, for instance, accesses student achievement reports at the highest average rate, only accessing about half as many student demographic, behavior, and attendance and teacher reports. This use pattern may not be as much a signal of strategic use as it is the Data Warehouse's orientation around student data and the district's emphasis on student achievement data use (Drake et al., 2014b). Across each of the report types, principals in the low use class access more reports in the Spring semester, a time when human capital decisions are more likely to be made. The timing of the increase (i.e., January, February, March) however, suggests that this increase in use may also be principals preparing for state testing in early April rather than any strategic human capital decision making.

The principals in the Middle-of-the-Road user type show consistent use of student data (i.e., student achievement, demographic, behavior, and attendance reports) across the school year, with roughly parallel lines across the two report categories, although they access more student achievement reports on average. Their average access to teacher reports, however, contains an important difference in their trajectory of use during the month of March, a time in the school year when principals start preparing their budgets and making decisions about teacher hiring, assignment, and dismissal (Figure 1)—all decisions that may be informed by information on teachers. It should also be emphasized that a majority of these reports are related to teacher value-added scores that are available to principals before the school year starts. Thus, the relatively sharp increase in use in March is suggestive of principals' in this group using teacher effectiveness data for the many human capital decisions they begin to make that month. The High Flyers' patterns of use shows remarkably similar trajectories across all three data report types. In addition, the shape of their access suggests that they access a lot of reports at the beginning of the school year and during the spring window leading up to state testing and the beginning of teacher hiring, assignment, and dismissal decision windows in March and April.

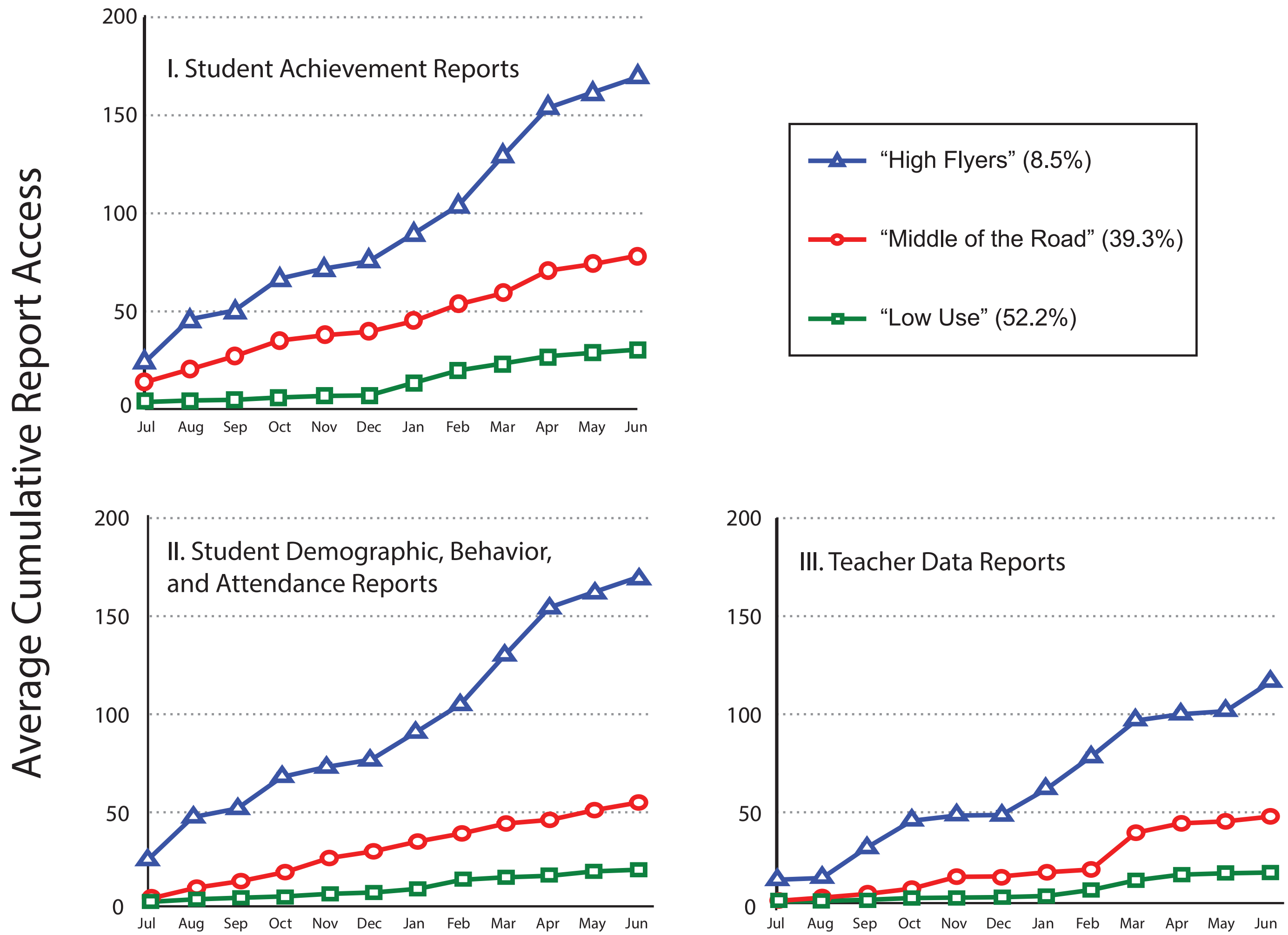

Figure 6: Average Cumulative Monthly Use, by Class & Data Report Type

To further examine these differences across Data Warehouse user type by month, Figure 7 displays bar graphs of the difference in average monthly use between Middle-of-the-Road and High Flyers, as compared with the Low Use class. The goal with these figures is to better see the differences in average monthly use. Thus, while we know that the cumulative totals are going to show relatively large average mean differences, here we are looking for the variation in these differences during each month of the academic school year to see if the size of the difference may align with key human capital decisions or student and teacher data availability.

For instance, student test score and teacher value-added data are made available on the Data Warehouse in late June, early July. In addition, the overall teacher evaluation score is made available in September, and the first benchmark exam is posted in late September. During each of these months, we see the "High Flyers" accessing teacher reports at high average rates, as compared with the "Low Use" principals. In addition, the "Middle-of-the-Road" class accesses an average of 5 to 10 more reports than principals in the low use class during July through October. And, like the line graphs above, we also see that March and April are months of large average differences between groups, which may be attributable to differences in data use with respect to teacher hiring, assignment, and dismissal.

In short, although each of the Middle and High Flyer classes are consistently using the data system more than the Low Use class for each of the three data types, there are times during the year when these differences are particularly noticeable. Reasons for these differences seem to include the timing of when data are made available and the time periods when key human capital decisions need to be made. Therefore, while the principals' self-reported measures do not seem to suggest differences in strategic behavior, the type of data principals access and the timing of when they access it seem to confirm strategic behavior around data access for human capital decision making. And, while these relationships are not formally testable with these data (i.e., human capital decisions or data availability **causing** more use), they do point to individuals making strategic choices about when they access data reports on students and teachers.

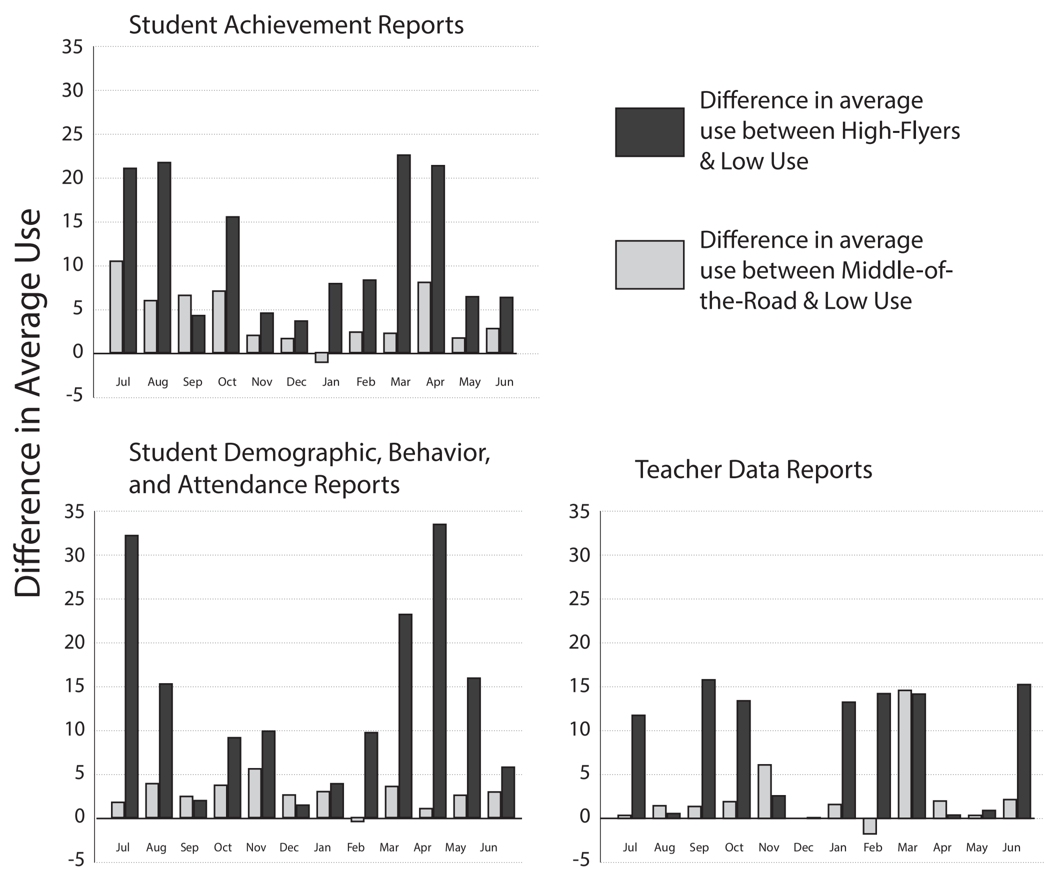

Figure 7: Difference in Average Monthly Use, by Class & Data Report Type

V.2.3 RQ4. How does school accountability and organizational context distinguish types of Data Warehouse users?

Accounting for principals' dispositions to use technology and the ways in which they strategically use data to make human capital decisions seems to ignore differences that might arise from the conditions found in their external environment, including the accountability pressure they feel, their school demographic composition, and school climate. As outlined in the conceptual framework, each of these may contribute to systematic variations in the ways in which principals access data on the Data Warehouse due to their differing environmental contexts and information needs (Belkin and Vickery, 1985; Leckie et al., 1996; Bosman and Renckstorf, 1996).

School Accountability & Types of Data Warehouse Users

One of the most common themes in the literature on data use in education is the way in which school accountability pressures may contribute to differences in teacher and school leader data use (Marsh, 2012; Fusarelli, 2008; Diamond and Cooper, 2007). Given the common narrative that is found in the data use in education literature, I might expect that lower performing schools or schools that feel more informal accountability pressures from their central office are found in disproportionately higher rates in the Middle-of-the-Road and High Flyer classes.

Table 10, however, suggests that the opposite may be true—principals' in the Low User class are in schools that perform at nearly half a standard deviation lower than the sample mean 3-year math and reading achievement (-0.44), principals in the Middle-of-the-Road class of users are in schools just below the sample mean (-0.04), and principals in the High Flyer class of users are in schools that score nearly a third of a standard deviation above the sample mean (0.32). This same type of relationship seems to be reflected in the extent to which principals' feel informal accountability pressures through their central office, with the Low Use class of users reporting higher average central office expectations than the other two classes of users (i.e., the “CO Presence Scale”), though these differences are quite small.

Table 10: School Accountability, by Type of Data Warehouse User

	Low Users		Middle Users		High Flyers	
Achievement (3 yr, Standardized)*	-0.44	(0.88)	-0.04	(1.06)	0.32	(1.28)
CO Presence Scale (Standardized)**	0.04	(0.63)	-0.01	(0.51)	-0.09	(0.66)
Justify hiring decisions**	1.80	(0.72)	1.81	(0.74)	2.14	(1.21)
Monitor completion of teacher obsv.**	3.43	(0.74)	3.19	(0.79)	2.71	(0.76)
Obsv. scores aligned with evidence**	2.43	(1.14)	2.63	(1.01)	2.14	(1.07)
Expects alignment achv. & obsv.**	3.40	(0.74)	3.59	(0.57)	3.57	(0.79)
Monitors past hires**	2.15	(1.00)	1.96	(0.71)	2.14	(1.07)
Asks to justify assignment decisions**	1.82	(0.83)	1.63	(0.79)	1.71	(0.76)
Asks to justify renewal decisions**	1.76	(0.85)	1.59	(0.84)	1.43	(0.53)
Produces reports to show effectiveness**	1.74	(0.93)	1.78	(0.85)	1.57	(0.98)
Compares PD decisions with teacher need**	1.91	(0.98)	1.85	(0.82)	2.00	(1.15)
Observations	34		27		7	

Note: Authors calculations. Standard deviation in parentheses.
*Standardized 3-year average of the percent of students rated proficient or advanced in math and reading/language arts for elementary and middle schools; standardized 3-year average ACT performance for high schools.
**Items based off a Likert Scale: 1=“Not at all”; 2=“Small extent”; 3=“Moderate extent”; 4=“Large extent”

The multinomial logit model predicting differences between the Low User class and the middle- and high-use classes suggests that the difference in school performance is significant, although the standard errors are large. The results from Table 16 suggest that a standard deviation increase in achievement is with a 50% increase in the odds of being in the Middle-of-the-Road versus Low Use class (RRR = 1.50, p = 0.13) and a 94% increase in the odds of being in the High Flyer versus Low Use class (RRR = 1.94, p = 0.08), given that the CO presence scale is held constant.

Therefore, it seems that contrary to research that finds a positive relationship between school accountability and data use, accountability pressure is negatively related to the Data Warehouse user types. Possible reasons for this difference and the limitations of these data will be discussed in the next section and chapter.

School Context & Types of Data Warehouse Users

Of course, student achievement is highly correlated with the schools’ student demographic composition and environment. Thus, it is difficult to make any conclusions

Table 11: Multinomial Logit Results for Measures Associated with School Accountability (DV = Predicted Class)

	Latent Class			
	Middle-of-the-Road		**High Flyers**	
	RRR	95% C.I.	RRR	95% C.I.
Achievement (3 yr, Standardized)	1.50	(0.89, 2.54)	1.94+	(0.92, 4.09)
CO Presence Scale (Standardized)	0.87	(0.36, 2.12)	0.68	(0.16, 3.00)
N	67			

Reference Category = "Low Use"
+ p<.10, * p<.05, ** p<.01

about school accountability pressures without also accounting for differences in the type of schools principals work in. A host of research articles on the information seeking behavior of professionals suggests that organizational environments contribute greatly to differing information needs; and, while unobserved, these differing information needs contribute to different patterns in information seeking behavior (Leckie et al., 1996; Belkin and Vickery, 1985; Bosman and Renckstorf, 1996). Furthermore, research on school effectiveness suggests that school level and student SES influence how principals work, including how they encourage teachers to use data (Heck, 1992; Hallinger and Murphy, 1986; Firestone and Wilson, 1989).

Table 12 shows differences in school context by Data Warehouse user type. These descriptive results suggest that Middle-of-the-Road Users and High Flyers are disproportionately found in middle and high school settings, which is reflected in differences in enrollment as well. Furthermore, the High Flyers are in environments with lower than average poverty and higher than average racial/ethnic entropy. The percent of students in special education is essentially equivalent across user types, and the percent EL, though higher for the High Flyers, has a relatively large standard deviation, which suggests few systematic differences between groups.

The results from these descriptive statistics suggest that school level, free-reduced price lunch percentage, and racial/ethnic entropy are school environmental measures that

Table 12: School Context, by Type of Data Warehouse User

	Low Users		**Middle Users**		**High Flyers**	
Enrollment	528.81	(281.88)	642.31	(463.50)	705.86	(275.08)
Middle/High School	0.33	(0.47)	0.59	(0.50)	0.57	(0.53)
FRPL (%)	0.78	(0.22)	0.75	(0.21)	0.58	(0.36)
Racial Entropy	0.77	(0.33)	0.93	(0.27)	0.99	(0.24)
SPED (%)	0.13	(0.13)	0.12	(0.05)	0.11	(0.02)
LEP (%)	0.13	(0.19)	0.12	(0.15)	0.19	(0.24)
Observations	34		27		7	

Note: Authors calculations. Standard deviation in parentheses.

may have the most significant bearing on differences in Data Warehouse user types. Given the limited sample size and the relatively strong correlation between these variables school level and racial/ethnic entropy (r = 0.22), I decided to estimate a multinomial logit model predicting user type using school level and free-reduced price lunch status. The results are shown in Table 17.

Although the standard errors are large, these results seem to confirm the finding that when compared with the Low Use class, the odds of being in the Middle-of-the-Road class increases significantly when principals are found in middle or high school settings, holding free-reduced price lunch percentage constant. This model also suggests that compared with the Low Use class, the odds of being in the High Flyer class decrease significantly as free-reduced price lunch percentage increases, holding school level constant.

In general, then, it appears that principals may utilize the Data Warehouse in systematically different ways in response to differences in their school environment, specifically their school level and percent of students receiving free and reduced price lunch.

Table 13: Multinomial Logit Results for Measures Associated with School Structure (DV = Predicted Class)

	Latent Class			
	Middle-of-the-Road		**High Flyers**	
	RRR	95% C.I.	RRR	95% C.I.
Middle/High School	2.99*	(1.15, 7.75)	2.85	(0.53, 4.09)
FRPL (%)	0.66	(0.08, 5.57)	0.05+	(0.00, 1.05)
N	82			

Reference Category = "Low Use"
+ p<.10, * p<.05, ** p<.01

A Note on School Climate & Types of Data Warehouse Users

While it seems reasonable to assume that measures of a school's environment extend beyond student demographic and structural characteristics, I find that there is no differences across various school climate measures by Data Warehouse user type (Table 14). Reasons for this seem to lie with the measures themselves and not with the hypothesized relationships. More specifically, as described in the Measures section, teachers generally have consistently positive views about their school's climate, and each of the different measures of climate are highly correlated. For example, the three scales used in this study—facilities, community support, and student conduct—all have correlations with each other ranging from 0.53 to 0.73. Therefore, while there is little difference between these measure by Data Warehouse user type, the measures themselves make it difficult to substantiate any claim regarding the relationship between school climate and principals' Data Warehouse user type.

Table 14: School Climate Measures, by Type of Data Warehouse User

	Low Users		Middle Users		High Flyers	
Facilities Scale	0.83	(0.09)	0.82	(0.10)	0.78	(0.13)
Instructional materials	0.83	(0.10)	0.80	(0.12)	0.79	(0.18)
Reliable instructional technology	0.77	(0.15)	0.78	(0.16)	0.64	(0.25)
Reliable communications technology	0.93	(0.07)	0.93	(0.08)	0.90	(0.06)
Equipment and supplies	0.76	(0.17)	0.76	(0.18)	0.70	(0.18)
Professional support personnel	0.81	(0.11)	0.81	(0.13)	0.81	(0.14)
Clean and well maintained	0.78	(0.17)	0.77	(0.20)	0.78	(0.20)
Adequate work space	0.90	(0.08)	0.88	(0.10)	0.84	(0.12)
Physical environ. of classrooms supports teaching and learning	0.87	(0.11)	0.87	(0.14)	0.85	(0.13)
Reliable Internet connection	0.79	(0.15)	0.75	(0.13)	0.70	(0.16)
Community Support Scale	0.80	(0.13)	0.79	(0.15)	0.81	(0.13)
Parents/guardians influential decision makers in school	0.61	(0.24)	0.59	(0.25)	0.62	(0.29)
Clear, two-way communication with parents/guardians	0.85	(0.12)	0.85	(0.15)	0.87	(0.11)
School encourages parental involvement	0.88	(0.12)	0.85	(0.16)	0.92	(0.09)
Teachers provide parents/guardians with information	0.94	(0.06)	0.92	(0.08)	0.94	(0.04)
Parents/guardians know what's going on in school	0.82	(0.16)	0.81	(0.18)	0.80	(0.16)
Parents/guardians support teachers	0.67	(0.20)	0.67	(0.23)	0.70	(0.24)
Community members support teachers	0.80	(0.15)	0.81	(0.15)	0.83	(0.15)
Community is supportive of school	0.80	(0.17)	0.82	(0.17)	0.81	(0.13)
Student Conduct Scale	0.80	(0.13)	0.76	(0.18)	0.79	(0.17)
Students understand expectations for conduct	0.84	(0.14)	0.81	(0.17)	0.85	(0.15)
Students follow rules of conduct	0.68	(0.24)	0.65	(0.29)	0.71	(0.31)
Policies and procedures are understood	0.84	(0.13)	0.80	(0.16)	0.83	(0.10)
School admin. consistently enforce rules	0.72	(0.19)	0.68	(0.23)	0.70	(0.22)
School admin. support teachers to maintain discipline	0.80	(0.17)	0.77	(0.20)	0.79	(0.18)
Teachers consistently enforce rules	0.83	(0.13)	0.75	(0.16)	0.74	(0.20)
School environment is safe	0.90	(0.10)	0.87	(0.18)	0.90	(0.13)
Observations	34		27		7	

Note: Authors calculations. Standard deviation in parentheses.
*Items based off proportion of teachers who agree or strongly agree with the statement

CHAPTER VI

DISCUSSION

VI.1 Review of the Study

This dissertation has been motivated by the need to better understand how principals access information on students and teachers from a Data Warehouse during a full academic school year. More broadly, this dissertation has been motivated by the need to understand if principals organize into homogenous types of Data Warehouse users, and the extent to which differences in these use types can be explained by the technology and technology use; strategic use by the principal to inform their human capital decision making; and/or the school context and environment, including the accountability pressures principals may be under. In this dissertation, I set out to answer four questions on principals' use of the Data Warehouse:

1. Are there significantly different types of Data Warehouse users among principals?
2. How do principals' personal inclinations to use technology and/or their views of the Data Warehouse distinguish types of Data Warehouse users?
3. How does principals' orientations towards data use for strategic human capital decision making distinguish types of Data Warehouse users?
4. How does school accountability and organizational context distinguish types of Data Warehouse users?

I find that in accordance with prior findings on U.S. adult's use of information and communications technologies (Horrigan, 2007), principals organize into one of three types of Data Warehouse users: (1) a Low Use class; (2) Middle-of-the-Road Users; and (3) High Flyers. **The Low Use** class contained a little over half of the principals in the sample (n = 43, 52.2%) and averaged a mean use of 7 times in July, 2013, with an increasing rate of use over the course of the school year, driven largely by higher average use in the spring semester. Principals in this group use the Data Warehouse an estimated **total** of only about 22 times during the school year. The second group, the **Middle-of-the-Road Users**, contained about 40% of principals in the sample (n=32, 39.3%) and averaged about 21 reports accessed in July alone, with a constant rate of increase of about 17 additional reports accessed each month. By the end of the year, these principals had accessed a total of about 215 reports. The final and smallest group, the **High Flyers**, only represented about 9% of principals in the sample. This group accessed an average of 86 reports in July, with a s-shaped use pattern over the course of the school year (i.e., more use at the beginning and towards the end of the school year), totaling about 511 accessed reports.

I hypothesize that this large disparity of how reports are accessed on the Data Warehouse between these three user types might be explained by a number of factors related to technology and/or principals' strategic responses to the need for information for (a) human capital decision making, (b) in response to school accountability pressures, and/or (c) due to differences in school context and climate. Summarizing across all of these factors, I find that principals in the Middle-of-the-Road and High Flyers user classes seem to differ from the Low Use class in a few systematic ways.

First, Middle-of-the-Road users access the TVA website at higher rates during the year; each additional use of the website is associated with a 7% increase in the odds of being in the Middle-of-the-Road user class (RRR = 1.07, p = 0.04). Compared with the Low Use class' slightly increasing trajectory in use over the course of the school year regardless of data report type, Middle-of-the-Road users also seem to break with their linear trend in Data Warehouse use in March by accessing more teacher reports, perhaps a signal of their strategic use of teacher data for hiring, assignment, and dismissal decisions. Finally, Middle-of-the-Road users tend to be in higher performing schools, and middle and high schools.[1] Therefore, differences in low- and middle-class user types seem to

[1] A multinomial logit regression of predicted class membership and these two variables of student achievement and school level confirms that each of these relationships still hold, holding the other constant. Thus, it is not just that the middle and high schools are higher performing, but that both of these variables seem to have an independent effect.

relate to principals' dispositions to use teacher data (i.e., through the TVA website and through increased use in March) and in response to difference school contexts, most notably those related to student performance and school level.

Second, High Flyers follow many of the same patterns as the Middle-of-the-Road users when compared to the Low Use class, although the magnitude of these relationships are often larger. For example, each additional use in the TVA website is associated with an increase in odds of being in the High Flyer class by 29% as compared to the Low Use class. Principals in the High Flyers also seem to be strategically accessing data at particular times in the year when either data become available (e.g. July, August, September, June) or human capital decision windows open (e.g., March). In looking across High Flyer's access to different types of data, however, it seems as though their use pattern follows a consistent trajectory regardless of the report being accessed. The High Flyer's also seem to be disproportionately located in lower poverty, higher achieving schools; middle and high schools; and schools with higher racial/ethnic diversity. Perhaps most importantly, principals in this group have on average about 5 years less experience than both the Middle-of-the-Road and Low Use classes. This equates to about a 23% reduction in the odds of being in the High Flyer class versus Low Use class (RRR = 0.77, p = 0.03) for each additional year of experience.

VI.2 Limitations

There are a number of important limitations to this dissertation study. First, although principal logins provide objective information on when principals access data reports on their district's data system, they do not guarantee that it is the principal themselves accessing the information. In this district, each principal receives a unique login and password; however, it is well-known that many principals give out this information to other faculty members, staff, and administrators. To the extent that this is occurring, these results over-attribute Data Warehouse access to the principal as an individual, and instead examine the use of these data systems by the principal and an unknown set of others. Informal conversations with district principals suggest that while the practice of giving out login information does occur, it is often to administrative staff and secretaries who pull reports for faculty meetings at the direct request of the principal. If this is the case, then others' access of the data would be functionally equivalent to the principal accessing it and would not bias principals' use of the Data Warehouse.

Second, as I will discuss in further detail below, principals may delegate their "data use" to someone else in the building or district. For example, it is common for some principals to use an assistant principal, teacher-leader, and/or data coach to access and analyze information on students and teachers (Means et al., 2010; Mandinach et al., 2012). If this were occurring, then measures of principals' data systems use through their own logins would be downwardly biased. In future work, I plan to exploring this limitation by interviewing principals with little to no data systems use throughout the school year to examine whether such a practice is occurring.

Finally, this dissertation does not provide any information on *how* principals use the information on the data systems to inform their decision making. That is, while I can determine what report or dashboard tools principals access, I do not know how that information is being used for decision making, or even what decision (or set of decisions) the information is being used to inform. In addition, while there has been a lot of attention on the use of academic data for decision making, it is clear that principals use many other forms of data and information to inform decisions—informal hallway conversations, information on parents, student health, or student interest inventories, for instance (Jimerson, 2014). In particular, recent work argues that alongside traditional measures of academic press, schools and districts should be developing more creative and robust measures of a school's culture of support and care (Murphy and Torre, 2014). Along with a principals' own professional judgment and past experience, these other "data" suggest that this dissertation may be as much about what is not found on the data system as what is found there. Low or highly variable rates of utilization suggest future avenues of research dedicated to uncovering not only principals' data use practices, but also those associated with data systems' development, training, and support.

VI.3 Implications: Exploring the Factors associated with Differences in Data Warehouse Users

Generational Differences

In considering the ascriptive characteristics of principals that may be linked to differences in adult's use of technology, there seems to be two generational differences that may influence differences in Data Warehouse use—age and years' experience. Principals who are younger, for instance, have been exposed to computers, the Internet, mobile devices and smart phones, and other digital technologies for a greater proportion of their life. As such, they may have natural dispositions and tendencies to use technology regardless of what it offers; that is, younger principals may use the Data Warehouse not necessarily because it has student and teacher data, but because of its technological properties—for these principals, using technology is the obvious and most intuitive way of doing work. Prensky (2001) argues that this immersion of technology has contributed to different brain structures and ways of operating among those of the rising generation of "Digital Natives," wherein "[they] are used to receiving information really fast. They like to parallel process and multi-task. They prefer graphics before text" (Prensky, 2001, p.1). All of these differences may contribute to the large gap between the High Flyers and Low Use classes. It may also explain the relatively small proportion of the sample in the High Flyer class, given that many of this rising generation are just entering the workforce and therefore would be found in smaller numbers among those appointed as executive principals in the district. Therefore, if age is a contributing factor to these differences in Data Warehouse use, then district's may respond by in the short-term by targeting training to older principals, though they may be confident that in the long-run, as more individuals from the rising generation ascend to the principalship, they can expect to see greater utilization rates.

Along with age, principal years' experience may contribute to differences in the ways in which principals' use the Data Warehouse. For example, principals with more experience may rely on old modes of work that are not driven by student or teacher performance information, including their own professional judgment, the relational and interpersonal nature of the job, and/or a more traditional emphasis on managing school operations (Hargreaves and Goodson, 2006; Terosky, 2013). Principals with more experience may also not buy into the data-driven movement, viewing it as a fad that will pass like the many other educational reforms that characterize American public education (Cuban, 2013). Principals with less experience are least removed from the classroom, and are therefore more likely to have been exposed to the data-driven movement as a teacher.

Yet, survey evidence from this study suggests that principals' positive feelings towards the Data Warehouse's expected performance does not vary significantly by Data Warehouse user type—it seems as though principals in the Low Use class are just as likely to agree that the system offers them information they could not access before and has made their work-life easier as the other middle- and high-use classes. Their differences in reported use of student achievement, teacher observation, and overall evaluation score for teacher hiring and dismissal, though relatively small, may suggest, however, that these principals are less inclined to use data for decision making. Nonetheless, these findings need to be balanced with the fact that principals in the Middle-of-the-Road user class have, on average, about the same number of years' experience as the Low Use class. Thus any differences need to be discussed in relation to the gap between the low- and middle-use classes and the high-use class. It seems clear that these 7 principals have less experience; what is not clear is whether this lack of experience contributes to a **need** to be more data-driven, or whether it is just a signal of a younger cohort of principals and their affinity for technology or data-driven decision making. Future work is clearly needed to explore these differences.

TVA Website & Access to Teacher Data

The findings from this study suggest each additional time a principal logs in to the website is associated with a 7% increase in the odds of being in the Middle-of-the-Road user class versus the Low Use class, and a 29% increase in the odds of being in the High Flyers versus the Low Use class, when all other variables are held constant. Practically speaking, the degree to which principals use one system seems to be strongly correlated with the degree to which they use the other. In this sample, for instance, the correlation is 0.58. There may be two reasons for the relationship between use of these two systems. First, it may be a signal of principals' pre-dispositions to use technology; that is, principals who are natural disposed to using one system are likely to use the other.

Second, it may not be as much a technology story is it is a data story. To examine this possibility, it is important to consider the differences in teacher data use between the low- and middle-classes of users, since the TVA website is limited to reports on teachers' value-added. Since we know that there will be raw differences reflected in their different classes of use, it is important to examine their trends in use. As Figure 6 demonstrates, the Low Use class follows a similar trend in use across all three report types; the Middle-of-the-Road users follow a consistent trend of use **except** for their access of teacher reports during the month of March, when their pattern breaks dramatically from the trend with a substantial average increase in use. As I discuss in the Results section, this may be driven by their use of teacher effectiveness data for human capital decisions. Regardless of the specific reason(s), this break in the trend suggests that these principals are interested not just in the technology, but in teacher data specifically—data that are also found on the TVA website.

Therefore, the relationship between TVA website use and Data Warehouse use may not just have implications for use of the two technologies, but more importantly about access and use of the teacher data found there, and the different ways principal may engage with these systems to access and ultimately use the data.

Middle & High Schools

The findings from this study suggest that the odds that a principal is in a middle or high school increases significantly as we move from the Low Use to Middle-of-the-Road Data Warehouse user classes, and from the Low Use to the High Flyers. It seems important to consider that principals of middle and high schools confront a very different organizational landscape than principals in elementary schools. There are generally more students and parents; more faculty and staff; athletic and academic programs to run; complicated course schedules to develop and maintain; career and college counseling to oversee; and higher rates of student dropout, mobility, and disciplinary issues; among others. These differences in organizational environment may contribute to principals different patterns of Data Warehouse use, as these principals may be more inclined to access data to make sense of the complexity of their organizational environment.

Higher Achieving, Lower Poverty Schools

The findings related to Data Warehouse use and student achievement and student poverty seem to run counter to the data use and school accountability narrative, wherein lower performing schools feel pressures to access and use data in ways that are systematically different than their higher achieving peer schools (Diamond and Cooper, 2007; Fusarelli, 2008; Firestone and González, 2007). Although this may have implications for data use more generally, it may be more a product of the time and effort required to login and use the system itself and not data use that is contributing to some of these differences. That is, principals in lower performing settings may have to deal with many challenges not found as frequently in higher performing settings, including students with poorer health, higher rates of misbehavior, higher mobility, and housing instability (Rothstein, 2004); and teachers who are on average less qualified and experienced (Lankford et al., 2002) and have higher turnover (Ingersoll, 2001; Guin, 2004) and absenteeism (Bruno, 2002). These challenges may contribute to their inability to use the system themselves at the same rates as those principals found in higher achieving school settings. As such, they may delegate data use to others by having them access reports on the Data Warehouse. Thus, it may not be that these principals are not using data, but that they are not accessing it themselves through this system. I develop this idea more in the next section.

In addition, it may be that the district is strategic about the types of principals that are being placed in higher achieving schools. That is, while there is a positive relationship between Data Warehouse user type and student achievement, it may be that the district is placing teachers and assistant principals who are younger and potentially more data-driven into higher achieving schools. This profile of a younger, data-driven school leader also seems to fit within the context of the neighborhoods and communities served by these higher achieving schools, where young middle- to upper-middle class families send their children to school.

VI.4 Implications: Exploring Under-Utilization in the Low Use Class

Districts and states all across the country are spending millions of dollars developing robust data systems like the one examined in this study. The goal of these systems is to present educators with real-time information on student and teacher performance (Means et al., 2010; Wayman et al., 2004). The extent to which these systems are being utilized has only recently been a topic of research. In studying teachers use of a data dashboard with student achievement data, both Tyler (2011) and Shaw and Wayman (2012) find that teachers average about 8 to 10 uses per month. Within the context of these districts and given the amount of money and time invested in developing these data systems, these levels of use were perceived by the districts and researchers as being low. I find that over half the principals only access a little over 20 reports during the school year, or an average of 1 to 2 reports a month. I believe there may be a number of factors that could contribute to this underutilization.

First, principals may not be using the system at desirable levels because they have not received the appropriate training and support. The process of “making sense” of technology includes what Niece termed “institutional mediation,” or the “extent to which ICT access is reinforced for...some groups...by institutionally enriched and supportive contexts” (Neice, 1998, p.9). In the district examined in this dissertation, training on the system is offered in monthly principals’ meetings, although interviews with principals and central office leaders suggests that these training sessions are short, demonstrative rather than participative, and inconsistent (Drake et al., 2014b). In addition to these meetings, the district has a dozen district-level data coaches to support teachers and principals in use of the Data Warehouse. As with other districts, however, data coaches in this district have large spans of control and are mainly deployed to support teachers’ use of student data for instructional improvement (Marsh, 2012; Mandinach et al., 2012; Weiss, 2012). Interviews with a random sample of principals in the district suggests that data coaches mainly interact with instructional coaches and teacher-leaders (Drake et al., 2014b).

Second, principals’ non-use of the Data Warehouse is as much a choice as a choice to use the system. As Orlikowski (1992) notes, “human agency is always needed to use technology and this implies the possibility of choosing to act otherwise” (p. 411). Thus, while there is evidence to suggest that differences in use between Data Warehouse user types may signal some form of strategic decision making on the part of middle- and high-class users, the converse may also be true—principals in the low-use class may be making strategic decisions about not accessing data reports from the Data Warehouse. Reasons for this strategic non-use behaviors might include principals who delegate data systems’ use to important others in their building and principals who do not value the data collected on the system.

Unlike teachers, principals have secretaries, assistant/vice-principals, and teacher-leaders that can pull data off data systems for them. Thus, low utilization may not be a sign of principals' non-use, but a sign of delegation. In this dissertation, I only measure reports accessed by individuals logged into principals' accounts. Importantly, if a principal relies on someone else to pull reports for leadership, faculty, and other administrative meetings, then I do account for this in my analysis. In fact, to the extent that reports on the Data Warehouse are static (e.g., pdf reports), it may not be the best use of principals' time to log onto the system themselves if the reports are ultimately made available to them for analysis and decision making.

Principals may also not value the data that are included on the system. Certainly, the accountability environment creates formal structures and processes that require principals' participation. For example, principals oversee the administration of a variety of data collected on students and teachers throughout the school year, including formative student assessments, teacher observations, and state standardized tests. Thus, principals have to engage in data collection and use to the extent that it is mandated by these accountability processes (Anagnostopoulos et al., 2013). But principals may not value this information, or at least may value other forms of data on their students and teachers more in making decisions.

As the primary function of schooling is not just test score performance, but positive outcomes for children, principals' may view their primary role as that of fostering and nurturing communities of pastoral care (Murphy and Torre, 2014). To do so, principals may focus on other data outside of the traditional test based measures included in the Data Warehouse, including students' prosocial values and reasoning (Baker et al., 1997), emotional well-being (Felner et al., 2007), satisfaction with school (Baker et al., 1997) and effective social skills (Demaray and Elliott, 2001). Principals may also work more on developing relationships with students, as strong relationships has been linked to greater student success (Hattie, 2013; Leithwood et al., 2010b). Thus, low utilization of the Data Warehouse may, in fact, be a signal from principals that they value other forms of data—data that are not only connected to improved outcomes for children, but have been also linked to student achievement specifically.

Importantly, the reason(s) for underutilization is going to influence districts' intervention(s) for increased use. If principals are not using the system because of a lack of training or support, the results from this dissertation suggest that they may respond by targeting training and support to individual principals who have more experience, are older, and are less inclined to other computer technologies in their work. In addition, this district may also consider using High Flyer principals in trainings sessions and/or in mentorship roles, develop more systematic and consistent training opportunities, and engage principals in using their own data during these training sessions. If the system is not being utilized because of data systems use through delegation, then districts will need to carefully consider if principals' own engagement with the system is important, or if it is enough for principals to have principals delegate data access and analysis to others. Finally, if the underutilization is the result of principals' discontent with the types of data included in the system, then districts might respond by co-constructing the development of the system and its content with principals in the district. In practice, the optimal decision may include each one of these actions, as principals may vary with respect to their reasons for low utilization.

Of course, the presence of multiple classes of data systems users does not prove that some users are underutilizing the system, or even that there is an optimal class of users. That is, while districts may assume that these rates are low, we cannot determine the optimal level of use until we examine the causal impact of data systems' use on job performance improvement. Thus, it is unclear if more data systems' use leads to more efficient (i.e., faster) access to the data and/or more effective practices. As a result, this study provides an important base upon which to explore these relationships and questions in future research studies.

VI.5 Contribution & Future Research

This dissertation contributes to and builds off the current research literature on data use in education by being among the first to examine principals' objective use of a Data Warehouse during an academic school year. Although the importance of school leaders in successfully supporting and implementing data use initiatives has been thoroughly documented (Marsh, 2012; Copland, 2003), less is known about how they actually use data to inform their work. Furthermore, that which is known is often based on principals' self-reports in surveys and interviews (Wayman et al., 2006; Means et al., 2010) or descriptions of evidence-based best practices (Goldring and Berends, 2008; Streifer and Schumann, 2005; Earl and Katz, 2002).

This dissertation breaks from this tradition by exploring how principals access data reports on teachers and students during a school year and empirically examines the extent to which data access varies by key personal and environmental characteristics. To do so, I used a latent class growth analysis, a methodology that is commonly employed in the psychological sciences, but has only recently begun to be used to examine the ways in which principals are trained and work (Urick and Bowers, 2014; Bowers and Sprott, 2012). This methodology is particularly well suited to examining outcomes that focuses on the relationships among individuals, and how individuals group into homogenous sub-groups (Nagin, 2005; Muthén and Muthén, 2000).

I find that in accordance with previous work on U.S. adults' technology use (Horrigan, 2007), principals form three distinct types of Data Warehouse users: Low Users, Middle-of-the-Road Users, and High Flyers. I also find that differences in these subgroups are empirically associated with differences in principals' ages and experience level; their orientations towards data use for human capital decision making; and their school contexts, including student achievement, poverty, and school level. Each of these findings has important implications for future work in the area of educational data use.

First, this dissertation highlights the importance of accounting for the ways in which principals receive data. Districts all across the country are investing millions of dollars in developing data warehouses, dashboards, and systems to support principals' access to and use of data (Wayman et al., 2004); nonetheless, training around these systems is weak (Means et al., 2010) and this dissertation finds that these systems seem to be underutilized by over half of principals. Future work might explore the reasons for this underutilization. In particular, future studies might explore the extent to which principals delegate data systems use to important others (i.e., data coaches, assistant principals, secretaries), and whether this delegation process is more efficient and/or effective than those who use the system themselves.

Other work in this area might continue to build on the research literature in the information sciences that explores how principals' own expectations and preferences shape information systems' use (Venkatesh et al., 2003, 2012). In this dissertation, I used the best available evidence to try to explore the extent to which differences could be accounted for by the **technology** or the **data**. Ultimately, I find that both the technology and the data seem to be associated with differences in Data Warehouse use. Nonetheless, decades of research in this area has created a number of survey scales and indices to measure engagement with technology and information use (Leckie et al., 1996; Davis, 1989). These scales might profitably be used to help determine the extent to which technology is a mediating factor in principals' access to and use of information on state and district data systems.

Second, this dissertation highlights the importance of accounting for school context in studies on data use in education. Empirical research on how school context contributes to data use practices is virtually non-existent (Mandinach et al., 2012). This dissertation finds that differences in principals' Data Warehouse use seems to be associated with both student achievement and school level. Future work might continue to build on this work by more systematically accounting for school context in exploring differences in data use practices and the success of data use interventions (c.f., Carlson et al., 2011).

Third, this study does not examine **how** principals actually use data once they access data reports on the Data Warehouse. That is, while I can determine what report or dashboard tools principals access, I do not know how that information is being used for decision making, or even what decision (or set of decisions) the information is being used to inform. Descriptive evidence on when and what types of information principals access suggests that they may be utilizing specific data (i.e., teacher value-added information) to inform decisions regarding teacher hiring and dismissal. Nonetheless, future work might build upon this work by examining how changes in principals' use of the system or the types of reports accessed is associated with future changes in principals' human capital (i.e., the distribution of effective teachers within the school; the number of highly effective teachers hired; etc.). This seems especially important given the investment in these systems that districts are making to develop and support data use.

Finally, while there has been a lot of attention on the use of academic data for decision making, it is clear that principals may draw upon and use many other forms of data and information to inform decisions, including informal hallway conversations, information on parents, student health, or student interest inventories (Jimerson, 2014). In particular, recent work argues that alongside traditional measures of academic press, schools and districts should be developing more creative and robust measures of a school's culture of support and care (Murphy and Torre, 2014). Along with a principals' own professional judgment and past experience, these other "data" suggest that this dissertation may be as much about what is not found on the data system as what is found there. Low or highly variable rates of utilization suggest future avenues of research dedicated to uncovering not only principals' data use practices, but how schools and districts can begin to leverage these systems to house new and varied sources of data that can be used to contribute to positive student outcomes.

Appendix A

A.1 IRB Approval

Vanderbilt University
Institutional Review Board

504 Oxford House Nashville, Tennessee 37232-4315
(615) 322-2918 Fax: (615) 343-2648
www.mc.vanderbilt.edu/irb

July 8, 2014

Timothy Drake, M.Ed.
LPO
207 A Payne Hall 37203-5721

Ellen B. Goldring
Leadership, Policy & Organizations
210 B Payne Hall 37203-5721

RE: IRB# 140923 [redacted] Principals' Use of Teacher Effectiveness Data for Human Capital Decision Making

Dear Timothy Drake, M.Ed.:

A designee of the Institutional Review Board reviewed the Request for Exemption application identified above. It was determined the study poses minimal risk to participants. This study meets 45 CFR 46.101 (b) category (4) for Exempt Review.

Any changes to this proposal that may alter its exempt status should be presented to the IRB for approval prior to implementation of the changes. In accordance with IRB Policy III.C, amendments will be accepted up to one year from the date of approval. If such changes are requested beyond this time frame, submission of a new proposal is required.

Please note, the federal regulations do not require updates to key study personnel for exempt research. As such, effective ***October 15, 2012*** , the Vanderbilt Human Research Protection Program will no longer ask for OR require administrative amendments to update KSP for those studies that qualify for an exemption under any of the categories for 45 CFR 46.101(b) (1-6).

DATE OF IRB APPROVAL: 7/8/2014

Sincerely,

Ray Woron

Raymond F Woron, MPH
Health Sciences Committee #2

RFW/rw
Electronic Signature: Raymond F Woron/VUMC/Vanderbilt : (07457AE52D11184737E603AA0E9EF884)
Signed On: 07/08/2014 01:43:45 PM CDT

Drake, Timothy IRB # 140923 1 07/08/2014

Figure 8: IRB Approval

A.2 Supplementary Tables

Table 15: Multinomial Logit Results for Measures Associated with Technology and Technology Use (DV = Predicted Class)

	Latent Class			
	Middle-of-the-Road		**High Flyers**	
	RRR	95% C.I.	RRR	95% C.I.
Years' Experience	0.97	(0.89, 1.06)	0.81+	(0.64, 1.02)
Data System (Scale)	0.56	(0.19, 1.63)	0.15	(0.01, 3.23)
TVA Use	1.08*	(1.10, 1.43)	1.25**	(1.10, 1.43)
N	65			

Reference Category = "Low Use"
+ p<.10, * p<.05, ** p<.01

Table 16: Multinomial Logit Results for Measures Associated with School Accountability (DV = Predicted Class)

	Latent Class			
	Middle-of-the-Road		**High Flyers**	
	RRR	95% C.I.	RRR	95% C.I.
Achievement (3 yr, Standardized)	1.44	(0.85, 2.43)	1.95+	(0.90, 4.23)
CO Presence Scale (Standardized)	0.80	(0.33, 1.95)	0.70	(0.15, 3.32)
N	65			

Reference Category = "Low Use"
+ p<.10, * p<.05, ** p<.01

Table 17: Multinomial Logit Results for Measures Associated with School Structure (DV = Predicted Class)

	Latent Class			
	Middle-of-the-Road		**High Flyers**	
	RRR	95% C.I.	RRR	95% C.I.
Middle/High School	2.33	(0.81, 6.71)	1.77	(0.29, 10.82)
FRPL (%)	0.56	(0.06, 5.24)	0.05+	(0.00, 1.29)
N	65			

Reference Category = "Low Use"
+ p<.10, * p<.05, ** p<.01

REFERENCES

Aaronson, D., Barrow, L., and Sander, W. (2007). Teachers and student achievement in the chicago public high schools. *Journal of Labor Economics*, 25(1):95–135.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2):179–211.

Anagnostopoulos, D., Rutledge, S. A., and Jacobsen, R. (2013). *The infrastructure of accountability: Data use and the transformation of American education*. Harvard Education Press Cambridge, MA.

Anderson, S., Leithwood, K., and Strauss, T. (2010). Leading data use in schools: Organizational conditions and practices at the school and district levels. *Leadership and Policy in Schools*, 9(3):292–327.

Au, W. (2007). High-stakes testing and curricular control: A qualitative metasynthesis. *Educational Researcher*, 36(5):258–267.

Baker, J. A., Terry, T., Bridger, R., and Winsor, A. (1997). Schools as caring communities: A relational approach to school reform. *School Psychology Review*.

Belkin, N. and Vickery, A. (1985). Precursors to information-seeking behavior: Information need. *Interaction in Information Systems: a Review of Research from Document Retrieval to Knowledge-based Systems*, pages 6–18.

Berlin, K. S., Parra, G. R., and Williams, N. A. (2014). An introduction to latent variable mixture modeling (part 2): Longitudinal latent class growth analysis and growth mixture models. *Journal of Pediatric Psychology*, 39(2):188–203.

Booher-Jennings, J. (2005). Below the bubble:educational triage and the texas accountability system. *American educational research journal*, 42(2):231–268.

Bosman, J. and Renckstorf, K. (1996). Information needs: problems, interests and consumption. *Acamedia Research Monograph*, 15:43–52.

Bowers, A. J. and Sprott, R. (2012). Examining the multiple trajectories associated with dropping out of high school: A growth mixture model analysis. *The Journal of Educational Research*, 105(3):176–195.

Broidy, L. M., Nagin, D. S., Tremblay, R. E., Bates, J. E., Brame, B., Dodge, K. A., Fergusson, D., Horwood, J. L., Loeber, R., Laird, R., et al. (2003). Developmental trajectories of childhood disruptive behaviors and adolescent delinquency: a six-site, cross-national study. *Developmental Psychology*, 39(2):222.

Bruno, J. E. (2002). Teacher absenteeism in urban schools. *Education Policy Analysis Archives*, 10:32.

Bucholz, K. K., Heath, A. C., Reich, T., Hesselbrock, V. M., Krarner, J. R., Nurnberger, J. I., and Schuckit, M. A. (1996). Can we subtype alcoholism? a latent class analysis of data from relatives of alcoholics in a multicenter family study of alcoholism. *Alcoholism: Clinical and Experimental Research*, 20(8):1462–1471.

Cannata, M. A., Rubin, M., Goldring, E., Grissom, J. A., Neumerski, C., and Drake, T. A. (2014). Using teacher effectiveness data for information rich hiring. Under Review.

Carlson, D., Borman, G. D., and Robinson, M. (2011). A multistate district-level cluster randomized trial of the impact of data-driven reform on reading and mathematics achievement. *Educational Evaluation and Policy Analysis*, 33(3):378–398.

Case, D. O. (2012). *Looking for information: A survey of research on information seeking, needs and behavior*. Emerald Group Publishing.

Clark, S. L. (2010). *Mixture modeling with behavioral data*. University of California, Los Angeles.

Clifford, M. and Ross, S. (2011). Designing principal evaluation systems: Research to guide decision-making. Washington, DC: National Association for Elementary School Principals.

Clogg, C. C. (1995). Latent class models. In *Handbook of statistical modeling for the social and behavioral sciences*, pages 311–359. Springer.

Coburn, C. E. and Turner, E. O. (2012). The practice of data use: An introduction. *American Journal of Education*, 118(2):99–111.

Cohen-Vogel, L. (2011). “staffing to the test:” are todays school personnel practices evidence based? *Educational Evaluation and Policy Analysis*, 33(4):483–505.

Compeau, D., Higgins, C. A., and Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly*, pages 145–158.

Compeau, D. R. and Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS quarterly*, pages 189–211.

Congress, U. (2009). American recovery and reinvestment act of 2009. *Public Law*, (111-5):111.

Copland, M. A. (2003). Leadership of inquiry: Building and sustaining capacity for school improvement. *Educational Evaluation and Policy Analysis*, 25(4):375–395.

Cuban, L. (2013). *Inside the Black Box of Classroom Practice: Change Without Reform in American Education*. Harvard Education Press.

Cuban, L., Kirkpatrick, H., and Peck, C. (2001). High access and low use of technologies in high school classrooms: Explaining an apparent paradox. *American Educational Research Journal*, 38:813–834.

Czaja, S. J., Charness, N., Fisk, A. D., Hertzog, C., Nair, S. N., Rogers, W. A., and Sharit, J. (2006). Factors predicting the use of technology: findings from the center for research and education on aging and technology enhancement (create). *Psychology and Aging*, 21(2):333.

Datnow, A., Park, V., and Wohlstetter, P. (2007). Achieving with data: How high-performing school systems use data to improve instruction for elementary students. *Los Angeles: Center on Educational Governance, Rossier School of Education, University of Southern California*.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, pages 319–340.

Demaray, M. K. and Elliott, S. N. (2001). Perceived social support by children with characteristics of attention-deficit/hyperactivity disorder. *School Psychology Quarterly*, 16(1):68.

Dempster, A. P., Laird, N. M., and Rubin, D. B. (1977). Maximum likelihood from incomplete data via the em algorithm. *Journal of the royal statistical society. Series B (methodological)*, pages 1–38.

Diamond, J. B. and Cooper, K. (2007). chapter 10 the uses of testing data in urban elementary schools: Some lessons from chicago. *Yearbook of the National Society for the Study of Education*, 106(1):241–263.

Donaldson, M. L. (2013). Principals approaches to cultivating teacher effectiveness constraints and opportunities in hiring, assigning, evaluating, and developing teachers. *Educational Administration Quarterly*, 49(5):838–882.

Drake, T. A., Cannata, M. A., Goldring, E., Grissom, J. A., Neumerski, C., and Rubin, M. (2014a). Timelines of talent management decisions and teacher effectiveness data availability. Unpublished Manuscript.

Drake, T. A., Cannata, M. A., Grissom, J. A., Neumerski, C. M., Rubin, M., and Goldring, E. (2014b). Southeastern urban district (deidentified): Landscape report. Unpublished Report.

Earl, L. and Katz, S. (2002). Leading schools in a data-rich world. In *Second International Handbook of Educational Leadership and Administration*, pages 1003–1022. Springer.

Easton, J. (2009). Using data systems to drive school improvement. In *Keynote address at the STATS-DC 2009 Conference, Bethesda, MD*.

Felner, R. D., Seitsinger, A. M., Brand, S., Burns, A., and Bolton, N. (2007). Creating small learning communities: Lessons from the project on high-performing learning communities about what works in creating productive, developmentally enhancing, learning contexts. *Educational Psychologist*, 42(4):209–221.

Firestone, W. A. and González, R. A. (2007). Culture and processes affecting data use in school districts. *Yearbook of the National Society for the Study of Education*, 106(1):132–154.

Firestone, W. A. and Wilson, B. L. (1989). Administrative behavior, school ses, and student achievement: A preliminary investigation. ERIC.

Fishbein, M. and Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Reading, MA: Addison-Wesley.

Fuller, E., Hollingworth, L., and Liu, J. (2015). Evaluating state principal evaluation plans across the united states. *Journal of Research on Leadership Education*, pages 1–29.

Fusarelli, L. D. (2008). Flying (partially) blind: School leaders' use of research in decision making. *Phi Delta Kappan*, 89(5):365–368.

Gefen, D. and Straub, D. W. (1997). Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS Quarterly*, pages 389–400.

Goertz, M. E., Olah, L. N., and Riggan, M. (2009). Can interim assessments be used for instructional change? *Consortium for Policy Research in Education*.

Goldring, E. and Berends, M. (2008). *Leading with data: Pathways to improve your school*. Thousand Oaks, CA: Corwin Press.

Goldring, E., Grissom, J. A., Rubin, M., Neumerski, C. M., Cannata, M., Drake, T., and Schuermann, P. (2015). Make room value added principals human capital decisions and the emergence of teacher observation data. *Educational Researcher*, 44(2):96–104.

Grissom, J. A., Rubin, M., Goldring, E., Drake, T. A., and Neumerski, C. A. (2014). Central office supports for data-driven talent management decisions: Evidence from the implementation of new systems for measuring teacher effectiveness. Under Review.

Grunow, A., Myung, J., Bryk, A. S., and LeMahieu, P. (2012). Data for improving human capital systems. *Carnegie Foundation for the Advancement of Teaching*. http://www.carnegiefoundation.org.

Guin, K. (2004). Chronic teacher turnover in urban elementary schools. *Education Policy Analysis Archives*, 12:42.

Hallinger, P. and Murphy, J. F. (1986). The social context of effective schools. *American journal of education*, pages 328–355.

Hargreaves, A. and Goodson, I. (2006). Educational change over time? the sustainability and nonsustainability of three decades of secondary school change and continuity. *Educational Administration Quarterly*, 42(1):3–41.

Hattie, J. (2013). *Visible learning: A synthesis of over 800 meta-analyses relating to achievement*. Routledge.

Heck, R. H. (1992). Principals instructional leadership and school performance: Implications for policy development. *Educational Evaluation and Policy Analysis*, 14(1):21–34.

Heilig, J. V. and Darling-Hammond, L. (2008). Accountability texas-style: The progress and learning of urban minority students in a high-stakes testing context. *Educational Evaluation and Policy Analysis*, 30(2):75–110.

Horrigan, J. B. (2007). A typology of information and communication technology users.

Iceland, J. (2004). Beyond black and white: metropolitan residential segregation in multi-ethnic america. *Social Science Research*, 33(2):248–271.

Ikemoto, G. S. and Marsh, J. A. (2007). Cutting through the data-driven mantra: Different conceptions of data-driven decision making. *Yearbook of the National Society for the Study of Education*, 106(1):105–131.

Ingersoll, R. M. (2001). Teacher turnover and teacher shortages: An organizational analysis. *American Educational Research Journal*, 38(3):499–534.

Jennings, J. L. and Bearak, J. M. (2014). teaching to the test in the nclb era how test predictability affects our understanding of student performance. *Educational Researcher*, page 0013189X14554449.

Jimerson, J. B. (2014). Thinking about data: Exploring the development of mental models for data use among teachers and school leaders. *Studies in Educational Evaluation*, pages 5–14.

Jung, T. and Wickrama, K. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and Personality Psychology Compass*, 2(1):302–317.

Kane, T. J., McCaffrey, D. F., Miller, T., and Staiger, D. O. (2013). Have we identified effective teachers? validating measures of effective teaching using random assignment. *Seattle, WA: Bill and Melinda Gates Foundation*.

Kimball, S. M. (2011). Principals: Human capital managers at every school. *Phi Delta Kappan*, 92(7):13–18.

Knapp, M. S., Copland, M. A., and Swinnerton, J. A. (2007). Understanding the promise and dynamics of data-informed leadership. *Yearbook of the National Society for the Study of Education*, 106(1):74–104.

Kreuter, F., Muthén, B., et al. (2007). Longitudinal modeling of population heterogeneity: Methodological challenges to the analysis of empirically derived criminal trajectory profiles. *Advances in Latent Variable Mixture Models*, pages 53–75.

Lachat, M. A. and Smith, S. (2005). Practices that support data use in urban high schools. *Journal of Education for Students Placed at Risk*, 10(3):333–349.

Laney, D. (2001). 3d data management: Controlling data volume, velocity, and variety. Technical report, Technical report, META Group.

Lankford, H., Loeb, S., and Wyckoff, J. (2002). Teacher sorting and the plight of urban schools: A descriptive analysis. *Educational evaluation and policy analysis*, 24(1):37–62.

Leckie, G. J., Pettigrew, K. E., and Sylvain, C. (1996). Modeling the information seeking of professionals: a general model derived from research on engineers, health care professionals, and lawyers. *The Library Quarterly*, pages 161–193.

Leithwood, K., Anderson, S. E., Mascall, B., Strauss, T., Bush, T., Bell, L., and Middlewood, D. (2010a). School leaders influences on student learning: The four paths. *The Principles of Educational Leadership and Management*, pages 13–30.

Leithwood, K., Patten, S., and Jantzi, D. (2010b). Testing a conception of how school leadership influences student learning. *Educational Administration Quarterly*, 46(5):671–706.

Licensure, I. S. L. (2008). Educational leadership policy standards: Isllc 2008.

Love, N. (2008). *Using data to improve learning for all: A collaborative inquiry approach*. Corwin Press.

Mandinach, E. B. (2012). A perfect time for data use: Using data-driven decision making to inform practice. *Educational Psychologist*, 47(2):71–85.

Mandinach, E. B., Gummer, E., and Northwest, E. (2012). Navigating the landscape of data literacy: It is complex. *WestEd and Education Northwest*.

Mandinach, E. B., Honey, M., and Light, D. (2006). A theoretical framework for data-driven decision making. In *annual meeting of the American Educational Research Association, San Francisco, CA*.

Marcinkiewicz, H. R. (1993). Computers and teachers: Factors influencing computer use in the classroom. *Journal of Research on Computing in Education*, 26(2):220–237.

Marsh, J. A. (2012). Interventions promoting educators use of data: Research insights and gaps. *Teachers College Record*, 114(11):1–48.

Means, B., Padilla, C., and Gallagher, L. (2010). Use of education data at the local level: From accountability to instructional improvement. *US Department of Education*.

Mendez-Morse, S. (1992). Leadership characteristics that facilitate school change. ERIC.

Moore, G. C. and Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, 2(3):192–222.

Morris, M. G., Venkatesh, V., and Ackerman, P. L. (2005). Gender and age differences in employee decisions about new technology: An extension to the theory of planned behavior. *Engineering Management, IEEE Transactions on*, 52(1):69–84.

Murali, V. (2014). Diving into data analytics tools in k-12. In *Retrieved from https://www.edsurge.com/n/2014-10-06-diving-into-data-analytics-tools-in-k-12*.

Murphy, J. (2005). Unpacking the foundations of isllc standards and addressing concerns in the academic community. *Educational Administration Quarterly*, 41(1):154–191.

Murphy, J. and Torre, D. (2014). *Creating productive cultures in schools: For students, teachers, and parents*. Corwin Press.

Murphy, J. F., Goldring, E. B., Cravens, X. C., Elliott, S. N., and Porter, A. C. (2011). The vanderbilt assessment of leadership in education: Measuring learning-centered leadership. *Journal of East China Normal University*, 29(1):1–10.

Muthén, B. and Muthén, L. K. (2000). Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and experimental research*, 24(6):882–891.

Nagin, D. (2005). *Group-based modeling of development*. Harvard University Press.

Nagin, D. and Tremblay, R. E. (1999). Trajectories of boys' physical aggression, opposition, and hyperactivity on the path to physically violent and nonviolent juvenile delinquency. *Child development*, 70(5):1181–1196.

Neice, D. C. (1998). *Measures of Participation in the Digital Technostructure: Internet Access*. University of Sussex, SPRU.

Odden, A. R. (2011a). Manage human capital strategically. *Phi Delta Kappan*, 92(7):8–8.

Odden, A. R. (2011b). *Strategic management of human capital in education: Improving instructional practice and student learning in schools*. New York: Routledge.

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science*, 3(3):398–427.

Porter, A., Goldring, E., Murphy, J., Elliott, S. N., and Cravens, X. (2006). A framework for the assessment of learning-centered leadership. *New York, NY: Wallace Foundation*.

Prensky, M. (2001). Digital natives, digital immigrants part 1. *On the horizon*, 9(5):1–6.

Ramaswamy, V., DeSarbo, W. S., Reibstein, D. J., and Robinson, W. T. (1993). An empirical pooling approach for estimating marketing mix elasticities with pims data. *Marketing Science*, 12(1):103–124.

Raudenbush, S. W. and Bryk, A. S. (2002). *Hierarchical Linear Models: Applications and Data Analysis Methods*. Sage.

Ravitch, D. (2011). *The death and life of the great American school system: How testing and choice are undermining education*. New York: Basic Books.

Reardon, S. F., Yun, J. T., and Eitle, T. M. (2000). The changing structure of school segregation: measurement and evidence of multiracial metropolitan-area school segregation, 1989–1995. *Demography*, 37(3):351–364.

Rivkin, S. G., Hanushek, E. A., and Kain, J. F. (2005). Teachers, schools, and academic achievement. *Econometrica*, 73(2):417–458.

Rockoff, J. E. (2004). The impact of individual teachers on student achievement: Evidence from panel data. *American Economic Review*, pages 247–252.

Rossi, P. H., Wright, J. D., and Anderson, A. B. (2013). *Handbook of survey research*. Academic Press.

Rothstein, R. (2004). Class and schools: Using social, economic, and educational reform to close the achievement gap. *Washington, DC: Economic Policy Institute*.

Schildkamp, K. and Kuiper, W. (2010). Data-informed curriculum reform: Which data, what purposes, and promoting and hindering factors. *Teaching and Teacher Education*, 26(3):482–496.

Shaw, S. and Wayman, J. C. (2012). Third-year results from an efficacy study of the acuity data system. Austin, TX: Authors.

Sichel, D. E. (1997). The productivity slowdown: is a growing unmeasurable sector the culprit? *Review of Economics and Statistics*, 79(3):367–370.

Streifer, P. A. (2002). *Using data to make better educational decisions*. Lanham, MD: Scarecrow Press.

Streifer, P. A. and Schumann, J. A. (2005). Using data mining to identify actionable information: Breaking new ground in data-driven decision making. *Journal of Education for Students Placed at Risk*, 10(3):281–293.

Teddlie, C. and Reynolds, D. (2000). *The international handbook of school effectiveness research*. Psychology Press.

Teddlie, C., Stringfield, S., and Reynolds, D. (2000). 5 context issues within school effectiveness research. *The international handbook of school effectiveness research*, pages 160–186.

Terosky, A. L. (2013). From a managerial imperative to a learning imperative experiences of urban, public school principals. *Educational Administration Quarterly*, pages 1–31.

Thompson, R. L., Higgins, C. A., and Howell, J. M. (1991). Personal computing: toward a conceptual model of utilization. *MIS quarterly*, pages 125–143.

Thorn, C., Meyer, R. H., and Gamoran, A. (2007). Evidence and decision making in education systems. *Yearbook of the National Society for the Study of Education*, 106(1):340–361.

Turner, E. O., Coburn, C. E., Supovitz, J., and Marsh, J. (2012). Interventions to promote data use: An introduction. *Teachers College Record*, 114(11):1–13.

Tyler, J. H. (2011). If you build it will they come? teacher use of student performance data on a web-based tool. Technical report, National Bureau of Economic Research.

Uline, C. and Tschannen-Moran, M. (2008). The walls speak: The interplay of quality facilities, school climate, and student achievement. *Journal of Educational Administration*, 46(1):55–73.

Urick, A. and Bowers, A. J. (2014). What are the different types of principals across the united states? a latent class analysis of principal perception of leadership. *Educational Administration Quarterly*, 50(1):96–134.

Venkatesh, V. and Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, 46(2):186–204.

Venkatesh, V. and Morris, M. G. (2000). Why don't men ever stop to ask for directions? gender, social influence, and their role in technology acceptance and usage behavior. *MIS quarterly*, pages 115–139.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, pages 425–478.

Venkatesh, V. and Speier, C. (1999). Computer technology training in the workplace: A longitudinal investigation of the effect of mood. *Organizational Behavior and Human Decision Processes*, 79(1):1–28.

Venkatesh, V., Thong, J. Y., and Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 36(1):157–178.

Wayman, J., Spring, S., Lemke, M., and Lehr, M. (2012). Using data to inform practice: effective principal leadership strategies. In *Annual Meeting of the American Educational Research Association, Vancouver, Canada*.

Wayman, J. C., Brewer, C., and Stringfield, S. (2009). Leadership for effective data use. In *Annual Meeting of the American Educational Research Association, San Diego, CA*.

Wayman, J. C., Midgley, S., and Stringfield, S. (2006). Leadership for data-based decision-making: Collaborative educator teams. *Learnercentered leadership: Research, policy, and practice*, pages 189–206.

Wayman, J. C. and Stringfield, S. (2006). Technology-supported involvement of entire faculties in examination of student data for instructional improvement. *American Journal of Education*, 112(4):549–571.

Wayman, J. C., Stringfield, S., and Yakimowski, M. (2004). Software enabling school improvement through analysis of student data.

Weiss, J. A. (2012). Data for improvement, data for accountability. *Teachers College Record*, 114(11):1–7.

Wilmore, E. L. (2002). *Principal leadership: Applying the new educational leadership constituent council (ELCC) standards*. Corwin Press.

Wohlstetter, P., Datnow, A., and Park, V. (2008). Creating a system for data-driven decision-making: Applying the principal-agent framework. *School Effectiveness and School Improvement*, 19(3):239–259.