PATHWAY TO ADOPTING LEARNING ANALYTICS: RECONCEPTUALIZING THE DECISION-MAKING PROCESS OF K-12 LEADERS IN NORTH TEXAS

by

JUSTIN THOMAS DELLINGER

DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in K-16
Educational Leadership and Policy Studies
at The University of Texas at Arlington

December, 2019

Arlington, Texas

Supervising Committee:

Yi Leaf Zhang, Supervising Professor
Bradley W. Davis
George Siemens

Abstract

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Justin T. Dellinger, Ph.D.

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Supervising Professor: Yi Leaf Zhang

Learning analytics has emerged as a data-driven way to improve learner outcomes over the past decade. However, as the adoption and implementation of learning analytics continues to surge, there are some significant barriers to this process, such as stakeholder buy-in, training, and support, concerns over privacy and ethical issues, the quality of tools provided by third-party vendors, and institutional capacity to collect and meaningfully analyze and interpret data. Poor implementation can increase inequities, squander public funding, foster stakeholder resistance around future initiatives, and ultimately lead to abandonment. Another challenge stems from the need for educators to not only understand a new tool, but the data that goes into and comes out of it. While there has been a growth in research on the adoption process in the higher education context, little has taken place in K-12. The purpose of this dissertation is to investigate key factors that may promote or hinder the adoption of learning analytics in North Texas K-12 schools by leaders. To do so, I explore psychosocial factors of leaders at the campus, district, and educational service center levels as well as how individual and school district capacities influence the decision to adopt learning analytics.

Given the exploratory nature of the study, I used a qualitative approach. My primary data source was semi-structured interviews with leaders in rural, suburban, and urban districts and educational service centers. I chose to investigate leaders over other stakeholders given their role in the adoption process, whereas other groups, such as teachers and students, play a bigger part in later implementation phase. Several key themes emerged from the data. The first theme was knowledge, where leaders' understanding of learning analytics and large-scale learning data varies significantly. The second was perceptions and attitudes, where leaders are conflicted about the available data that they have and perceive numerous challenges, opportunities, and concerns about the use of learning analytics in a K-12 context. The final theme is capacity. While North Texas school districts in this study have a robust technology infrastructure and mechanisms for adopting new tools, there are discrepancies between small, rural districts and large, suburban and urban districts with regard to their capacity to adopt learning analytics. The findings also indicate that the participants have greater technology literacy than data literacy.

This study has numerous implications for policy, practice, and research. Given the limited nature of the size of the study, additional research needs to take place in order to better develop a broader framework that can guide leaders in the adoption process. This research could further investigate differences between leader characteristics, such as educational background and perceived innovativeness, and district characteristics, such as size and funding. Additional studies could also investigate the relationship between leaders/districts and third-party vendors who offer learning analytics solutions, which are often quite expensive and do not always fit in a certain district's context. Finally, with the rise of data and technology in K-12 districts, educator preparation needs to include more emphasis on understanding and thinking critically about learning data as a core, 21st-century skill.

Acknowledgements

I am forever grateful to all of those who have supported me through my doctoral journey. There are more people who have made an impact on this process over the past three years than I can include here, but your support, guidance, encouragement, and accountability helped me get to the finish line, and I will never forget it.

First, I would like to thank my dissertation committee. My supervising professor, Dr. Yi Leaf Zhang, provided steadiness during rocky times, accountability to push me through, and great suggestions to improve the quality of my work. It was in my first semester with Dr. Bradley W. Davis where the beginnings of this research project began to take shape and he helped guide my subsequent independent study, where I read over 100 articles, books, and other materials on related topics. Dr. George Siemens, as my boss in the LINK Research Lab, introduced me to the field of learning analytics, connected me with prominent scholars, got me moving with walking meetings, and encouraged me to pursue my doctorate.

Next, I would like to express my sincere gratitude to the students as well as current and former faculty of the K-16 Educational Leadership and Policy Studies (ELPS) doctoral program for providing feedback and friendship along the way. Additionally, Dr. Barbara Tobolowsky, our doctoral program advisor, gave incredibly constructive feedback and was always available to listen and help whenever she could.

I was also blessed to receive funding from a number of sources that helped me grow as an emerging scholar and would like to recognize each of them. The ELPS department and College of Education provided financial support to present my early-stage research in graduate student tracks at two regional academic conferences. The Phi Kappa Phi Honors Society and the Office of Graduate Studies awarded grants that funded travel to present research, transcription services that significantly cut my time to degree, and my writing group. Finally, the Society for Learning Analytics Research funded my travel to the 8th International Learning Analytics and Knowledge Conference in Sydney, Australia to participate in the doctoral consortium and present my project during the poster session. Many thanks for all of your support!

To now Dr. Melissa Thompson, Dr. Rachel Jones, Dr. Ashley Carter, and Dr. Rebekah Chojnacki, I appreciate all of your support and feedback during our weekly writing group meetings over the past year. It was amazing to see your research develop since we started the doctoral program and I am so proud that we all made it through in under 3.5 years. It is a testament to all of your hard work. I appreciate your friendship and eagerly look forward to seeing your careers grow.

Finally, I would like to thank those in the LINK Research Lab, University Analytics, and Center for Research on Teaching and Learning Excellence for your support and feedback throughout the duration of my program. In particular, Dr. Pete Smith, thank you for the coffee talks and reference suggestions; Elizabeth Powers, thank you for helping me secure grants to fund my research and for your recommendations along the way; and T. Lisa Berry for your insights and providing some work flexibility at critical times this past year.

Dedication

To my wife, Erica, thank you for your love, patience, support, proofreading, and prayers. There is no way that I could have made it through the program this quickly without all that you have done along the way. I look forward to all of the free time that we get to have together now that I am done with graduate school. Rawr!

To my son, Thomas, thank you for your patience and understanding while I worked to finish my doctorate. I know that it has been hard to have me locked away in the study or spending late nights up in the office, but I also look forward to spending time with you and having you beat me at Mario Kart. Thanks for being my study buddy up in the LINK Lab on the weekends. You are truly the bestest in the westest.

To my parents, Donna and Tad, thank you for modeling hard work and persistence, and for your continued support as I changed doctoral programs. Thank you for always being willing to listen and for helping with childcare when I needed it so I could get a few more hours to work on my writing.

To the rest of my family, my brother Chris, Grandma Ruth, Uncle Joe, Aunt Becky, Aunt Meg, and Uncle Jim, thanks for your support, interest in my research, and love throughout the process. I am proud to be the third Dellinger generation with a Ph.D.!

To all of my friends, whether at South Oaks or Nick and Dana in Austin, thank you for your prayers, friendship, and help keeping me sane with things like game nights!

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Chapter One

Introduction

Learning analytics is a rapidly emerging field of research and practice. Broadly defined, learning analytics is the collection, measurement, and analysis of data to improve learning in a range of contexts (Sclater, Peasgood, & Mullan, 2016; Siemens, 2012), which includes formal academic settings in schools, colleges, and universities, and informal settings in massive open online courses (MOOCs). Learning analytics has progressively grown as a means to aid the reskilling of the current workforce ("Corporate Learning Analytics Trends," 2018).

Given that the field is still relatively young, there are a number of different conceptions about learning analytics. Some might describe institutional or academic analytics (Campbell, DeBlois, & Oblinger, 2007), and they could include using digital trace data in ways that are more organizational or business-focused than for learning itself, such as reporting (Siemens et al., 2011). There is also a significant overlap with the field of educational data mining (Liñán & Pérez, 2015). However, early learning analytics researchers stressed these distinctions and to avoid “trivial measures” that do not advance teaching and learning (Gasevic, Dawson, & Siemens, 2014, p. 69). For the purposes of this study on the adoption of learning analytics, I focus on two key areas: data and the tools/technology used to collect, measure, and analyze it. For example, an educator can make use of a tool, such as a learning management system (e.g., Canvas), along with the student data it collects, and a dashboard (e.g., Inspire for Faculty by Civitas Learning) that provides real-time feedback, tracks course trends, and helps inform possible interventions for at-risk students to improve their outcomes. This educator would need to understand the two technologies, the data used by the tools, and the information that they generate.

Researchers and practitioners have increasingly used digital large-scale learning data and analytics tools and methods as data-driven approaches to gain a better understanding of the learning process and address educational challenges (Wise, 2019). Learning analytics can improve teaching and learning (Jimerson & Childs, 2017; Kalil, 2012; Office of Educational Technology, 2017), providing meaningful impact ranging from individual students to institutions (Bienkowski, Feng, & Means, 2012; Campbell et al., 2007; Gunawardena, 2016; Mandinach, 2012; Park & Shelton, 2012; Picciano, 2012; Sclater & Mullan, 2017). However, the growth of large-scale data analytics and the interweaving of data collectors into schools presents significant challenges for educators (boyd & Crawford, 2012; J. Hall, 2017; Madden, 2017).

As learning analytics adoptions have expanded, questions over issues such as privacy and data use and ownership have similarly increased (Jones & Salo, 2018; Jutting, 2016; Slade & Prinsloo, 2013). Furthermore, sensitive student information has become more vulnerable to data breaches in schools that are ill-equipped to provide adequate security (Federal Bureau of Investigation, 2018; Gardner, 2017; Nazerian, 2018). These issues can foster a lack of trust and buy-in, which can create barriers to the adoption of learning analytics (Drachsler, 2016; Kharif, 2014; Pardo & Siemens, 2014).

Another challenge that educators have experienced is the inundation of educational technology and data culture without corresponding pre-service and on-campus training, as well as lacking sustained support and resources for effective use, which consequentially contributes to failed adoptions (Aldunate & Nussbaum, 2013; Catalano, 2018; Mandinach & Gummer, 2013; Shattuck, 2010; Standards Required for the Principal Certificate, 2016; Stevenson, 2017). Teachers, in particular, often feel anxiety from initiatives such as these due to a perceived increase in workload and decrease in autonomy (Chiu, 2017). While *big data* (large-scale data sets) and analytics hold great potential to help students, all stakeholders ultimately have to know how to use the information, which is a significant challenge for institutions (B. C. Phillips & Horowitz, 2017; Prinsloo & Slade, 2017a; Terrell, 2016; West, Huijser, & Heath, 2016).

Finally, vendors drive many technology adoptions, and third-party companies often occupy the gap between researchers and practitioners (Siemens, 2012). Learning analytics companies typically employ black box systems, which remain proprietary and lack accessibility to researchers and practitioners, and greatly hinder improvements to learning analytics techniques. Even more problematically, these systems may also promote inequities and impair student outcomes by overgeneralizing interventions and failing to take factors such as different contexts into account (Ferguson et al., 2014; O'Neil, 2016; Tawfik, Reeves, & Stich, 2016). It is unclear how prepared leaders are to adequately assess these products during the adoption process, which may ultimately negatively impact student outcomes and lead to subsequent abandonment.

As the field of learning analytics has continued to mature, researchers have started investigating these three challenges to increase the likelihood of successful adoption for institutions that are beginning the process or want to improve their current systems (Ochoa & Wise, 2017). However, most of the research concentrates on the higher education context. My dissertation focuses on the K-12 context to address the gap in the literature.

Statement of the Problem

Over the past few years, researchers have begun to develop evidence-based frameworks for the adoption and implementation of learning analytics (Scheffel, 2017; Sclater et al., 2016; Tsai, Gasevic, Muñoz-Merino, & Dawson, 2017; Universities UK, Civitas Learning, & Jisc, 2016). Scholars situated these frameworks at different stages in the learning analytics adoption process, which include the factors that lead to the decision to adopt or reject, implementation (i.e., putting adopted technology into use), and confirmation (i.e., evaluating adoption), as shown in Figure 1.1 (Miranda, Farias, de Araújo Schwartz, & de Almeida, 2016; Rogers, 2003). For example, if a school district decides to adopt learning analytics, the next phase is implementation. Stakeholders across the district would be the ones to do so, and therefore, the adoption is still at risk if there are failures during the implementation stage. For the purposes of this dissertation, I do not explore the connections with later phases, but future research should investigate implementation and confirmation stages in order to paint a complete picture of the larger adoption process.

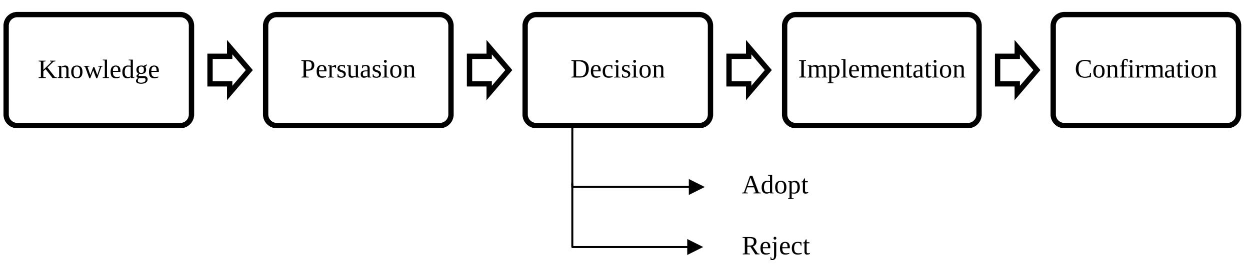

Figure 1.1 Adapted Innovation-Decision Process (Rogers, 1983, p. 165).

While these frameworks have begun to help guide administrators in colleges and universities through these stages, research occurred in the higher education context and it is unclear if they are applicable to K-12 administrators who wish to formally adopt learning analytics (Baker, 2018; Chiu, 2017; Ferguson et al., 2014; Kharif, 2014; Law, Niederhauser, Christensen, & Shear, 2016). School administrators are unlikely to have appropriate resources to guide a successful learning analytics adoption, which could potentially negatively impact both the process and the outcomes. Tsai and Gasevic (2017) found that higher education leaders often do not have the ability to implement learning analytics effectively in a strategic manner, and it is reasonable to suggest the same results for K-12.

Because educators need to understand learning analytics tools as well as the data that they use and generate, it is imperative to understand the dual impact on the adoption process. Stakeholder buy-in and support, concerns over privacy and ethical issues, and the quality of tools can all serve as barriers. However, there are significant opportunities that come from a data-driven decision-making standpoint. Therefore, I situate this study at the nexus between data and technology and their perceived challenges and opportunities as they relate to the decision-making process.

Theoretical Framework

For this dissertation, I define learning analytics as the collection, measurement, and analysis of data to improve learning in a range of contexts. Educational technologies and tools play an important role in two ways. First, they can potentially collect the large-scale digital learning data, and second, they provide a way to analyze this vast amount of information that educators can use to inform their practice. Therefore, stakeholders that adopt learning analytics have to be able to use both types of tools and have a fundamental understanding of the data collected and used. Given that investigating the adoption of learning analytics involves two separate elements, data and tools, and that few implementations have taken place to date in the K-12 space, the development of a new framework could prove useful for leaders who want to adopt it going forward.

Since stakeholders play an important role in the adoption process, my primary focus is on the individuals and how they facilitate or impede the uptake of learning analytics. In my dissertation, I investigate leaders, but future investigations should include other stakeholders. These leaders include both campus- and district-level administrators, such as principals, directors of curriculum and instruction, or assistant superintendents, and regional service centers. While school districts (or sometimes specific campuses) are the main mechanism to adopt a technology, individual educators are the ones who implement it; without buy-in and proper support, adoptions will ultimately fail.

I adapt the Multicultural Competency framework (The Tilford Group, 2001) for my dissertation as a model to qualitatively examine the capacity for leaders to adopt learning analytics. The framework was developed at Kansas State University as a way to promote diversity on campus and help students succeed in a diverse world (S. Khan, 2003; The Tilford Group, 2018b). This project conducted qualitative research that questioned around 200 participants in 22 focus groups that took 90 minutes each. The investigators recruited from all colleges, the library, and deans council and included students, faculty, staff, and administrators. The overarching research goal was identifying critical competencies needed by individuals and in different colleges. To ensure trustworthiness, the investigators conducted pilot testing and emphasized neutral questioning, and later conducted a thematic analysis that led to three main categories and 14 overall competencies (The Tilford Group, 2001, 2018b, 2018a). Overall, this framework is well-used in industry and at universities, but has not been used much for educational research. Some examples include advising (Carlstrom, 2005), public administration, relations, and affairs education (Rice, 2007; M. A. Rivera, 2010; M. Rivera, Johnson III, & Kodaseet, 2015; Toth, 2009), and use by academic colleges (Carter, Hobbs, & Wiley, 2019; "History of the Tilford Group at PSU," n.d.).

The Multicultural Competency framework has three key areas: knowledge, personal attributes, and skills (The Tilford Group, 2001). Knowledge primarily focuses on awareness and understanding. Attributes includes the traits needed for something. Skills consists of behaviors and performance tasks. While multicultural competencies are not directly comparable to learning analytics adoption, these three areas provide a solid framework to understand conditions. For example, are leaders aware of learning analytics and how they are used? Do leaders have the skills to use new technologies and large-scale learning data? Do leaders feel that they have support to complete required tasks?

For this study, I use these three categories to investigate the role of psychosocial factors and capacity to understand the position of the individual in the adoption process. First, I explore knowledge as understanding about large-scale learning data and analytics. Second, I adapt attributes to include perceptions, attitudes, and participant background, such as their education and experience. Finally, I adapt skills to include capacity for learning analytics, such as district support, training, guidelines, and adoption mechanisms, and individual use of data and technology. In the following sections, I further explain the concepts of psychosocial factors and capacity as well as personal attributes that I use to address the theoretical framework.

Psychosocial Factors

These factors include different standardized measures used in technology adoption literature. *Perception* (Venkatesh, Morris, Davis, & Davis, 2003) is another factor that I define as how an individual sees something. Negative perception, even unwarranted, may lead one to reject something. *Attitudes* (Ajzen, 1991; Venkatesh et al., 2003) are affective in nature, where an individual has either a positive or negative appraisal of something, and he/she may or may not be influenced by preconceived ideas. Finally, *understanding* in this paper entails cognitive knowledge about a topic. In this case, does an individual know what learning analytics is and how they should use it? Given that learning analytics is a new field, many educators likely do not have a firm grasp on what it is and how it might work. Other psychosocial factors, such as *Motivation* (Sørebø, Halvari, Gulli, & Kristiansen, 2009) and S*elf-efficacy* (Bandura, 2006) are often studied with these other factors, but they were not fully explored in this study and are areas that warrant further investigation.

Capacity

There are few empirical studies that explore the readiness of school districts to adopt learning analytics; most sources come from industry reports. Researchers have explored the role of the district at large in technology adoption and fostering data culture, but given that learning analytics requires both, it warrants further investigation. To do so, I examine school district capacity for learning analytics adoption, any related policies and processes, and demographic characteristics. It is important to note that some campuses have the ability to adopt their own significant technologies. Given that this is a qualitative study, I obtain this information from the perspectives of the district leaders.

Higher education studies, such as the SHEILA Project and results from a pilot study in my 2018 Advanced Qualitative Methods doctoral course, illuminate a number of areas that school districts need in order to better adopt learning analytics. Staffing, funding, training, implemented technology, and stakeholder buy-in are all areas that require attention before a successful adoption. For example, if a district has sufficient staffing and funding, a solid technology infrastructure, and an energized group that will implement learning analytics, the lack of sufficient training and support can potentially doom an adoption due to ineffective use or growing dissatisfaction.

Given the increased attention to ideas, such as data security and privacy ranging from local to federal levels, school districts will likely face greater scrutiny if they have insufficient policies and regulations in place to guide various stakeholders. Additionally, it is important to determine what processes school districts have with regard to change management and technology adoption. For example, do campus leaders have a voice in a district's technology adoption process?

Leaders have a wide range of experience and expertise with educational technology tools and learning data. Understanding this area is useful to see how much of a role that experience plays in the adoption of learning analytics. For example, are individuals in schools with significant technology investment better prepared to employ learning analytics? Or does an existing data culture in a school district better facilitate adoption? Therefore, these are relevant areas for investigation.

Personal Attributes

Personal attributes include factors that might have an influence in the adoption process. For the purposes of this study, I include: working for service center or district, administrative position level (e.g., district or campus), administrative position (e.g., curriculum and instruction, assistant principal), job title, school level (e.g., primary, secondary, both), sex, age, and educational background. I also ask leaders to rate their attitude towards new technology. In Chapter Four, I share these attributes in biographical descriptions of each participant.

Purpose and Research Questions

The purpose of this dissertation is to investigate key factors that may promote or hinder the decision to adopt learning analytics in K-12 schools by administrators. In order to ascertain these factors, I use the Multicultural Competency framework (The Tilford Group, 2001), which includes knowledge, attributes, and skills. These can fall under two key areas: psychosocial factors and capacity. To address these areas, my study consists of two research questions:

1. How do psychosocial factors (perceptions, attitudes, and understanding) of K-12 campus and district leaders in North Texas promote or hinder the decision to adopt learning

analytics tools and large-scale learning data?

2. How does internal (skills) and district (guidelines, training, support, technology and data infrastructure) capacity promote or hinder K-12 leaders' decision to adopt learning analytics in North Texas school districts?

Overview of Method

For this dissertation, I use a qualitative approach and exploratory design. Given the limitations of different adoption and diffusion models for the learning analytics context, this method is applicable. The process for this approach includes iterative data collection and analysis, where each contact shapes the results until saturation occurs.

The primary source of data is semi-structured interviews with campus- and district-level K-12 leaders and staff at regional educational service centers. The participants for the study come from a range of small, rural to large, urban districts (e.g., small (< 12,000 students), medium (12,000 – 25,000 students), and large (>25,000 students)), and different job levels and types. The sample includes leaders from districts in the Regions 10 and 11 Educational Service Centers, located in North Texas. I record all interviews electronically, and then transcribe and clean them to remove potential identifiers and non-relevant text, and share with participants for review. I then use open and axial coding to categorize information, explore causal conditions, and identify contexts (Creswell & Poth, 2017).

Personal Relevance

Since my dissertation is a qualitative study, it is important for me to ensure trustworthiness of the data analysis by acknowledging my background related to this topic (Creswell & Poth, 2017). This can help to clarify experiences and biases that could shape my interpretation of the data that I collect. For the purposes of this study, I share my K-12 and learning analytics backgrounds.

After graduating from college, I worked in a school district in North Texas as a junior high teacher and coach for four years. My campus was a visual arts and technology magnet and a very successful Title I school. I really enjoyed my time as a teacher, but ultimately left to pursue a full-time master's degree while continuing to work as a tutor and substitute teacher in the same district. Although I decided to remain in higher education and begin a doctoral program, I have a continued interest in K-12 and have maintained my teaching certificates.

While employed at my university, I have had the privilege of working under one of the founders of the first learning analytics society and organizers of the first conference of the new field. Working in the research lab, I gained exposure to the field as it continued to emerge over the past decade and have made numerous personal and research connections across the globe. Additionally, I have been able to attend and present in the last five annual conferences and funded by the Society for Learning Analytics Research to participate in a learning analytics summer institute and a doctoral consortium. Over the past two years, I have also helped to develop a series of open online courses on learning analytics methods and a master's of science new program proposal for my university. During my doctoral studies, I initially focused on ethical issues of learning analytics and large-scale data, but began to investigate the adoption process and capacity building while partnering with scholars who investigated these phenomena in a higher education context.

Delimitations

In this study, I conduct my research in a North Texas public school context. Focusing on public school districts omits charter and private schools, which can potentially have different standards. While each public school district is unique, they have some common elements, including public funding, no applications or costs to attend, local governance, and adherence to all state and federal educational laws. The North Texas region provides a focused area of study in order to reasonably complete a dissertation while offering a large number of diverse school districts.

Additionally, concentrating solely on leaders provides a useful and manageable focus for understanding technology adoption in school districts. While teachers and students make more sense in the implementation phase, most of the decision-making process for technology adoption currently occurs at the administrative/leadership level (Carlson, 2019; Davies & West, 2017; Msila, 2011). The sampling of these leaders is heterogeneous to help improve the broader application of the results by including a wide variety of perspectives, ranging from campus to central office positions.

Limitations

While there is a significant corpus of literature about technology adoption in a K-12 context, there is little research on the use of learning analytics. Use of an exploratory research design helps to address the gaps as an early contribution to the literature. Additionally, focusing only on leaders excludes three of the largest stakeholder groups: teachers, students, and parents. Future investigations should take these stakeholders into consideration by testing the findings in additional contexts and further refining models to include perspectives from non-leaders. Moreover, access to participants was often difficult to attain as many school districts have their own research review boards. This process increased the time needed for the study and resulted in changing targeted districts due to some conditions that arose during the process.

Significance of the Study

As districts continue to adopt technologies centered around large-scale learning data and analytics, they can potentially reduce long-term costs, intensify the impact of educators and curriculum, increase student data protection and privacy, and improve student outcomes (Nunn, Avella, Kanai, & Kebritchi, 2016). The data generated in these systems can help produce actionable interventions that address the specific needs and contexts of different schools (Macfadyen, 2017), and effective use may promote interoperability and break down traditionally siloed systems over time. This could enable school systems to intensify their focus on all students, especially in districts that concentrate more on at-risk populations.

A few Texas schools have begun to develop predictive models using integrated datasets ("The K-12 Analytics Research Consortium," n.d.). I argue, however, for significant research efforts statewide and for leaders to inform their learning analytics adoption by using evidence-based, cutting-edge research to ensure effectiveness and legitimacy (Tsai & Gasevic, 2017). This research project is an important step in helping school districts increase the likelihood of successful adoption.

Summary

In this chapter, I outlined the research problem, theoretical framework, purpose of the study, personal relevance, and significance. In the following chapters, I provide background through a literature review, my research design and methodology, the findings of the study, and a discussion including implications for research, policy, and practice. Overall, I investigate key factors that may promote or hinder the adoption of learning analytics in K-12 schools by administrators in order to help guide future leaders. Given the dearth of literature on this topic, this dissertation can serve as a foundation for future research into the adoption of learning analytics by school districts.

Chapter Two

Literature Review

In this section, I first describe the development of big data and how learning analytics developed out of its rise. Next, I share ethical considerations around the use of large-scale learning data and analytics, followed by issues for public trust and data security. In the subsequent section, I review prominent investigations into learning analytics adoption and the frameworks that researchers developed in the higher education space. I then discuss the context for the future adoption of learning analytics in K-12 schools. Finally, I share different adoption theories and why they are not sufficient for this study.

Development of Big Data and Learning Analytics

One of the current leading trends in education is the rise of big data (boyd & Crawford, 2012). This term has become a prominent buzzword since 2011, and while people may have a rudimentary understanding of what it is, there is no unified definition (Ward & Barker, 2013). In an attempt to synthesize the field, Ward and Baker (2013) highlight three key areas in their survey of big data definitions by focusing on a dataset's size and complexity, as well as the technology used to process it. Smartphones and social media are exemplars from recent years that epitomize these areas in a few ways. First smartphones provide a significant quantity of data given their continuous connectivity to networks. Ownership for all adults in the United States increased from 35% to 68% between 2011 and 2015 (Anderson, 2015), and 95% of 2018 teens report that they own or have access to one (Anderson & Jiang, 2018). Second, social networking sites such as Facebook and Twitter also gather a massive amount of information and have experienced tremendous growth for adults from 7% in 2005 to 65% in 2015 (Perrin, 2015). Users have increasingly woven these data collectors, among many others, into their everyday lives and provide corporations rich sets of information about their consumers (J. Hall, 2017).

Boyd and Crawford (2012) mention, however, that big data is really less about size and more about the "capacity to search, aggregate, and cross-reference large data sets" (p. 663). Data for the sake of data is relatively useless, but power (both altruistic and adverse) comes from its analysis. Therefore, it is not as much the data itself as how one uses it. These authors suggest that the process of using technology to help analyze large data might provide better tools and services for societal improvement, but they might also create negative repercussions. For example, the medical community might use big data to more effectively identify causes of cancer, but an insurance company might use similar data as a mechanism to deny coverage for treatments. In essence, the recent explosion of data mining and analytics implementations has the potential to provide insight into individual and societal issues at large, but it can also amplify power asymmetry between people and companies, institutions, and governmental agencies. Therefore, it is important for stakeholders to have conversations around ethical frameworks for these analytics implementations. Given the fiduciary role that educational institutions have with their students, these frameworks are especially relevant (Prinsloo & Slade, 2015).

The field of learning analytics grew out of the rise of big data and has developed into a significant domain of research and practice. Scholars created the Society for Learning Analytics Research that organizes growing annual conferences and workshops that highlight current research completed in educational contexts (SoLAR, 2016). Institutional policy leaders have initiated implementations that use learner data to try to further understand the learning process in order to improve student outcomes and resources (Buckingham Shum & Ferguson, 2012). Although most scholars have focused on course activity and achievement, incorporating different data sources such as biometrics, class attendance, eating habits, and use of social networks can provide broader contexts to understand students and how they learn (Siemens, 2012). Rubel and Jones (2016) have gone as far as stating that learning analytics implementations might provide a limitless scope of useful information. While there is a great capacity for data collection and analytical tools, being a young field presents a number of challenges.

One issue for research in an emerging field is the lack of established standards (Peña-Ayala, Cárdenas-Robledo, & Sossa, 2017). Ward and Baker (2013) found varying definitions for big data and the same applies to learning analytics. This is due to the development of new models, frameworks, and principles, as well as shifting conceptualizations by a progressively broadening group of stakeholders. Terms such as "academic analytics" and "organizational analytics" have complimented learning analytics, but the latter can also encompass all analytics implementations (i.e., Macro, Meso, and Micro) (Buckingham Shum, 2012; Campbell et al., 2007; MacNeill, Campbell, & Hawksey, 2014; Sclater et al., 2016). Scholars in the Society for Learning Analytics Research originally defined the field as the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens, 2012, p. 4). These early adopters utilized more of a learner-centered approach for research that they could apply broadly instead of siloed solutions at specific campuses. These scholars also called for more open datasets that institutions could share, further expanding potential impact. Slade and Prinsloo (2013) have defined learning analytics as "the collection, analysis, use, and appropriate dissemination of student-generated, actionable data with the purpose of creating appropriate cognitive, administrative, and effect support for learners" (p. 1512). This perspective is more organizational and administrative, which makes it slightly more complex in nature given the broader focus.

While both definitions emphasize employing data to promote student success, the means to do so is murky, and it has become increasingly difficult to separate different types of analytics implementations from each other given the prospect for overlap. Data collection and analysis around business functions might have connection to academic support or studying the learning process (Boulton, 2016). For example, if an information technology office collects data about wireless internet access points in order to assess student usage to determine needed infrastructure upgrades, this information might also be useful for student support specialists and educational researchers. Staff could determine how much time students spend on campus, and where and with whom they spend it. Examination of this data could also highlight what types of websites that students visit, what kinds of devices they use, and their utilization of support resources. Researchers could use the data to study residential versus commuter status, mobile technology accessibility, and what times of day students best complete school-related tasks. The interconnectivity of datasets holds great power for analysis, but these connections illuminate a number of ethical considerations.

Ethical Issues for Learning Analytics Adoption

K-12 schools face a number of challenges when adopting learning analytics. First, school district administrators can fall into the trap of what Morozov (2013) has coined *technological solutionism*, where leaders attempt to solve broad, complex problems using a narrow digital solution (Hardesty Bray, 2007; Morozov, 2013). In an educational context, an example might be adopting a new technology and expecting it to improve retention in schools without understanding additional complex factors in play. These factors could include effective practices in online environments, who has access to these systems outside of the classroom, if this tool is the right fit for all stakeholders in a specific context, what data sources to use, or the quality of algorithms used for personalized learning. Ultimately, technological solutionism may lead to overgeneralized, simplistic interventions through a one-size-fits-all mindset (Gasevic, Dawson, Rogers, & Gasevic, 2016). Snowden and Boone (2007) argue that this mindset is evident in poor leadership practices. Additionally, a lack of patience to sufficiently test and roll out deployments could result in the rejection of a tool, such as learning analytics, if it is deemed ineffective.

Educational technology may simultaneously hold great potential for some, but may also further social inequity for others. Tawfik, Reeves, and Stich (2016) suggested that using technology for interventions to improve student outcomes may favor certain populations and that educators and scholars need to pay more attention to the design, development, and adoption of these tools. For example, Du, Ge, and Xu (2015) found that students' diverse cultural backgrounds played a significant role in success in online collaborative education settings, but had largely been ignored prior to their study. Tawfik, Reeves, and Stich (2016) advised that professional development is a key component for the use and integration of new technology, but there is unequal access to high-quality training sessions in struggling districts, which may increase the likelihood of failed implementations and inadvertently widen achievement gaps in lower-performing school districts. In another example, educational leaders have used digital dashboards for the last two decades to display relevant data to policy makers (Harel & Sitko, 2003; Rothman, 2015; Shacklock, 2016). However, do these leaders know what data sources these dashboards present? Can they see any biases of algorithms and profiles? Do they have employees with sufficient understanding of complex technological systems (Knight, 2017)? These are important considerations that policy makers need to address when considering learning analytics adoption at their institutions. If they do not address them, adoption could lead to the potential for discrimination and unethical use of data.

Prinsloo and Slade (2017b) further suggest that educators need to move beyond ethics of justice and more towards an ethics of care. The authors suggest that justice entails an "autonomous, objective, and impartial agent" while care involves more attention to "the complexities, intersectionality, and multidimensional nature of individuals" (pp.115-116). Doing so considers the individual at the center instead of viewing them as one in a larger number. It is important to separate both justice and care from legal frameworks, as laws can reinforce changing power structures (for example, Plessy v. Ferguson permitting state-sponsored segregation). It is unclear if federal and state laws are sufficient enough given the rapid change in the use of educational technology and large-scale learning data.

If schools can attempt to support learning through tracking and connecting most elements of a student's life at their campus, from time spent in class, to meals consumed at the cafeteria, to books checked out in the library, to visits to the nurse, to meetings with counselors, then privacy issues become a very real concern (Jones & Salo, 2017; Jutting, 2016; Quinton, 2015). Perhaps even more disconcerting to some is that data collected by analytics software can fall outside of federal definitions of educational records, which opens the door for broader data-sharing opportunities. When agencies, institutions, and companies can readily profile individuals, and research and share data without student or parental consent, it can create visions of an Orwellian Big Brother that undermine public trust through fear of decreased civil freedoms (boyd & Crawford, 2012). Some practical examples of fear for United States residents might be the recently nullified internet privacy legislation that allows service providers to use and sell personal data (Fung, 2017), the Obama Administration's call for an "all-hands-on-deck" Big Data Research and Development Initiative to better extract knowledge from complex datasets (Kalil, 2012), or the Chinese social credit system, where citizens would receive a rating based on daily behaviors that could impact their ability to get a job or receive a loan (Chin & Wong, 2016). The belief by leaders that innovative technologies can solve educational problems does little to assuage these fears and can actually continue to perpetuate them (Watters, 2015).

Public Trust and Data Security

As institutions increasingly collect information about their students, staff, and faculty, the public has begun to seriously question the process (Quinton, 2015). The analytics organization inBloom, created from a $100 million investment by the Bill and Melinda Gates Foundation, shut down after three years of existence, mostly over concerns of data privacy despite no documented misuse (Kharif, 2014). A simple lack of building trust with stakeholders was enough to bring down a well-funded non-profit entity. Higher-profile examples of misuse of data only magnify concerns. As Kurshan (2016) noted, scholarships.com shared student data with a company that sold information including health, religion, and sexual orientation to advertisers. Google mined over 30 million student emails through an educational application for advertising purposes (Kurshan, 2016; Straumsheim, 2014a). Piazza, an online environment designed to connect students with instructors and support staff, has also sold student information from the University of California, Berkeley to recruiters (McNeal, 2016).

Concerns over data are not only limited to students as educators are also subject to overly-deterministic analytics. For example, teachers in New York faced a publicly published scale that ranked them by name solely based on comparing student standardized test scores (Hancock, 2012). Hancock mentions that the data was "riddled with mistakes, useless sample sizes, flawed measuring tools, and cavernous margins of error" that could be off by 35% for math teachers and as much as 53% for English teachers (para. 7). She goes on to mention that the New York State Board of Regents discredited standardized tests due to inflation and not factoring in other, more complex issues, but the publication of these rankings potentially had condemning effects on teacher evaluations and misleading the public.

Since 2014, legislators have increased the number of student privacy bills amidst growing concerns tied to data access from high profile cases (Kurshan, 2016). Most recently, the current discrimination lawsuit against Harvard University opened a trove of de-identified, undergraduate data, including academic, extracurricular, and demographic information (McNeal, 2016). Despite the mounting political influence, Mitchell Stevens, Director for Digital Research and Planning at Stanford University, suggested that “cobbling together existing regulations won’t solve the problem” and that “it’s not that the ethics have changed – it’s the conditions under which ethical decisions have to be made” (Straumsheim, 2014b, para. 5-6). Essentially, just because institutions can quietly collect and analyze huge amounts of data, it does not mean that they should (boyd & Crawford, 2012). At present, however, there is enough leeway in the Family Educational Rights and Privacy Act (FERPA) to allow it in most cases. This gray area is where ethical decisions are paramount, often skirting the lines of legality and morality (Anderson, 1996).

Some recent efforts to address these issues include the U.S. Department of Education guidelines for student digital data privacy (Privacy Technical Assistance Center, 2014), but there are still great challenges such as ownership turnover in educational technology companies (Kurshan, 2017). One recent example is NetDragon’s buyout of Edmodo, a tool for teachers and administrators to communicate and collaborate with students and parents (Corcoran & Wan, 2018). There are significant concerns about what private data NetDragon, as a Chinese company, can access from its millions of users. However, there are also recent policy developments around data privacy such as the European Union’s General Data Protection Regulation (GDPR, 2016), which passed April 2016, and seeks to empower individuals and protect them from current, under-regulated practices. This includes actions such as the right to be forgotten or notification of data breaches.

Recent cyber-attacks, such as the “WannaCry” ransomware that affected almost 100 countries or the 2016 United States election hacks, have led to increased public awareness over online vulnerability. Gardner (2017) suggests that “the rise of big data has also abetted hacker’s efforts” and technological advancements have made it possible for hackers to quickly steal terabytes of data to sort later on, rather than just specific targets. (para. 8). Schools and postsecondary institutions have worked to curb hacking through encryption, cloud-based storage, and other means, but currently struggle to fill qualified data security positions on campus (Gardner, 2017; Picciano, 2012). Use of third-party vendors further complicates the issue since the educators do not directly control all aspects of security and privacy (McNeal, 2016). Leaders and researchers who want their students to wear devices that collect physiological data may not fully grasp a company’s data-collection, storage, and sharing practices, and compulsory data collection might jeopardize privacy (Lomas, 2016). For example, Oral Roberts University required first-year students to wear fitness trackers that synchronized with a D2L gradebook and monitored their data, including steps and heartrate (“Oral Roberts University integrates wearable technology,” 2017). If institutional leaders were not aware of the fitness tracker’s data practices, personal student data might have been inadvertently shared and students would not have an option to opt out. Therefore, data security is another important factor to consider as institutions rapidly digitize courses and educational records.

Given the use of large-scale data and reliance on third-party vendors, considerations such as these should increasingly become important aspects of educational policy going forward regarding learning analytics tools. The development of evidence-based frameworks can serve as a key starting place for school districts that are interested in using such tools. Examples of these frameworks in a higher education context are in the following section.

Learning Analytics Adoption Research

Researchers have focused on issues such as ethics, privacy, and codes of practice more than adoption, but all are relatively new topics of inquiry in the field of learning analytics (Pardo & Siemens, 2014; Prinsloo & Slade, 2017b; Rubel & Jones, 2016; Sclater et al., 2016). Ochoa and Wise (2017) defined each of these as meta-issues for the field of learning analytics that interweave to varying degrees, but adoption has the least established research. To date, there have only been a handful of systematic studies examining adoptions that have taken place in Australia and Europe, and each of these studies took place in a postsecondary context. I discuss each study in this section.

Dawson and his colleagues ("Learning analytics in Australia home page," 2017) examined the state of learning analytics adoption in 32 Australian postsecondary institutions. They also investigated barriers and challenges for universities that intended to use learning analytics (Dawson, 2015). The researchers found that any attempts at a full, systematic implementation were typically in the early stages of the process and that few universities had enough sophistication in their deployments to significantly improve the learning process and student outcomes. Furthermore, they found that quick recognition of and responses to an institution's organizational culture and critical stakeholders improved the quality of an implementation. They proposed a model for sustainable uptake that emphasized resource flow, key influences, and reinforcing processes in a highly complex system. This project was the first of its kind and is significant for highlighting the complexities of learning analytics and providing the first model for sustainable uptake.

Researchers for the project “Supporting Higher Education to Integrate Learning Analytics” (SHEILA) (“SHEILA Project About Page,” n.d.) initiated a similar study in a European context that included 78 senior leaders at 51 postsecondary institutions in 16 countries. When working to create a policy framework for learning analytics adoption, they conducted interviews, utilized a group concept mapping activity, and distributed an institutional survey; they found similar results to the Australian study (Tsai, Moreno-Marcos, Tammets, Kollom, & Gašević, 2018). In an early phase of the project, Tsai and Gasevic (2017) identified and reviewed eight policies, and found challenges with systematic implementations, a lack of formalized guidelines, weak communication between stakeholders, and few pedagogical-based approaches which indicated a lack of teacher involvement. They also uncovered a dearth of necessary skills to use tools and data, and the need for solid evaluation of adoption efforts that could inform the field and raise awareness of key challenges and opportunities. Like the Australian project, this project was a significant undertaking and has provided an alternative model for learning analytics adoption and implementation. For the purposes of my research, I adapt their interview protocol to fit the K-12 context that I investigate. From a viewpoint solely focused on grade levels, it is not a perfect fit, but does inform key elements that should apply in both school and higher education institutions.

Halliday and Anderson (2016) also explored creating a framework to help higher education institutions in the United Kingdom use learning analytics. The authors used a grounded theory approach for qualitative and quantitative data and focused on the use of visualization tools and learning analytics at one institution. In the end, they found the need to observe and collect data on students throughout a course to paint a more complete picture of the learning process, but there was no conclusive data to build an effective framework. This project was not especially useful for informing my work.

Many of the frameworks for learning analytics use have come from groups such as Jisc and the Learning Analytics Community Exchange. Jisc is a membership organization in the United Kingdom that seeks to further digital learning in higher education. Niall Sclater has primarily driven the work on learning analytics that includes topics such as code of practice, the effect of the European Union's General Data Protection Regulation (GDPR), and assessing impact on student outcomes (Sclater, 2018, 2018; Sclater & Bailey, 2015; Sclater & Mullan, 2017; Sclater et al., 2016). The Learning Analytics Community Exchange, or LACE, is a project funded by the European Union aimed at integrating learning analytics and educational data mining research, identifying future work in the fields, building communities of practice, and developing a knowledge base grounded in evidence ("About LACE," n.d.). LACE has since established a model that examines research, policy, and practice as it relates to ethical issues, supporting implementations, and future planning. The organization also includes an evaluation framework for learning analytics, developed by Scheffel (2017), to offer a way to "measure and compare the impact of learning analytics on educational practices of learners and teachers" ("Evaluation framework for learning analytics," n.d.). While the work has primarily focused on the higher education space, LACE is one of the few groups of scholars that have explored the public school context where I situate my research.

Adoption of Learning Analytics in K-12

While much of the research has focused on higher education, K-12 school districts have also begun to adopt learning analytics. Research organizations, such as the recent K-12 Horizon Report (Freeman, Adams Becker, Cummins, Davis, & Hall Glesinger, 2017) argue that school leaders are eager to use learning analytics to guide decision-making and empower teachers through the use of learning data to improve instruction and student outcomes. In this report, the authors identified the increasing integration of learning analytics on campuses over the next three-to-five-years, meaning that now is a critical time to begin to inform implementation with evidence-based research. Funders have also increased focus by targeting topics such as digital courseware (e.g., digital literacy tools - Hunt, 2015) and data-driven education that promotes interoperability (e.g., Baur, 2018; “Data-driven education,” n.d.).

In addition to foundation funding, the passing of Every Student Succeeds Act (ESSA) in 2015 also provided a boost to educational technology as the federal government placed greater emphasis on the use of these tools (Levin, 2016). Therefore, understanding the relationship between vendors and K-12 leaders is an important factor as more educational technology companies develop learning analytics products (Cavanagh, 2014). ESSA signals future policy implications for schools going forward with regards to the use of large-scale learning data and analytics.

Increased public accountability centered on educational budgets significantly contributes to the continued use of technology in school districts, and administrators’ mismanagement of funding can lead to trouble with state and federal policymakers (Ross, 2015). In a broader context, technology waste (e.g., underutilization, misuse, abandonment) due to poor implementation may have a significantly negative effect on schools that already have scarce resources, which can create further resistance to needed changes (Mohammed & Harlech-Jones, 2008). Additionally, teachers often do not have the necessary support to implement technology in their practice effectively, increasing reluctance to adoption and reducing the chance of successful integration (Mohammed & Harlech-Jones, 2008; Norris, Sullivan, Poirot, & Soloway, 2003). A recent report by Baker and Gowda (Tate, 2018) found that teachers and students have never used a majority of purchased educational technology when they analyzed “1.48 million hours of technology usage by 390,000 students across 48 U.S. school districts” (para. 2). A key reason for this is that school leaders are not “intentional about tracking and assessing data” (para. 13). Ultimately, Baker stressed that local implementation conditions have a lot to do with successful integration of tools.

Finally, the lack of support and resources for the effective use of educational technology, much less large-scale learning data and analytics tools, presents significant challenges for adoption due to anxiety and buy-in from teachers (Aldunate & Nussbaum, 2013; Chiu, 2017; Mandinach & Gummer, 2013; Shattuck, 2010; Stevenson, 2017). The data culture cannot only reside with the teachers and needs to exist at all stakeholder levels, with administrators taking the lead in the process (Cho & Wayman, 2014; J. Sun, Johnson, & Przybylski, 2016). In particular, Cho & Wayman (2014) argue that change agency comes from stakeholders and not through the technologies themselves, and that *sensemaking*, how people ascribe meaning to experiences, plays a significant role in data use and technologies. It is important to remember that not all educators who actively use technology to enhance pedagogy are the same and typically fall into different subgroups, such as evaders (Graves & Bowers, 2018). This means that school leaders need to be intentional with the way that they support teachers and other stakeholders with the use of new technological approaches, such as learning analytics.

As evidenced by work on learning analytics adoption in the higher education space, critical elements exist that can influence K-12 schools as well. All of the literature reviewed above applies to varying degrees in both contexts. However, it is also valuable to identify key differences between K-12 schools and post-secondary institutions to promote a better understanding of significant challenges, opportunities, and perspectives that may facilitate and ensure successful learning analytics adoption. I discuss the similarities and differences in the final chapter.

Theories for Adoption

To better understand factors around the adoption of learning analytics, a theoretical framework can provide structure to understanding the topic under investigation. Currently, there are numerous technology adoption frameworks that researchers have used in an educational context. Many of the theories around adoption and diffusion are born out of *Social Cognitive Theory* (Bandura, 1989; Straub, 2009), which is not sufficient alone for this research investigation. Some of the most commonly used examples include *Innovation Diffusion Theory* (Rogers, 2003), *Concerns-Based Adoption Model* (G. E. Hall, 1979), *Technology Acceptance Model (TAM)* and *Unified Technology Adoption and Use Theory (UTAUT)* (Venkatesh et al., 2003).

Rogers's theory is incredibly complex and difficult to utilize for a small-scale research investigation (Straub, 2009). It incorporates a large number of variables and Straub argues that it is not useful for understanding how to facilitate adoption; rather, it can help with knowing why an adoption occurred (p. 632). This theory could be useful for a larger study as learning analytics begin to mature in the K-12 space, but is not well-suited for my dissertation.

While Hall's theory (1979) appears to be more applicable, given the perspective of adoptees instead of a large system, the fact that learning analytics use is not widespread in a K-12 setting creates limitations around the idea of *levels of use*. Although it is difficult to ascertain who is using learning analytics tools and large-scale learning data, *innovation characteristics* and *stages of concern* are useful constructs. However, omitting a key factor would weaken the investigation.

TAM and UTAUT are both based on the *Theory of Reasoned Behavior* (Ajzen, 1996; Straub, 2009), where behavior derives from attitudes and social norms. *TAM* investigate perceived ease of use/self-efficacy and perceived usefulness (Davis, 1989) where *UTAUT* focuses more on key determinants (performance expectancy, effort expectancy, social influence, facilitating conditions) and moderators (gender, age, experience, and voluntariness of use)(Venkatesh et al., 2003). Scholars have raised concerns about using *TAM* in an educational context (Straub, 2009; Wolski & Jackson, 1999), while others have worked to extend and combine to address the limitations of the model (Tan, 2013). Venkatesh et al. (2003) created *UTAUT* to integrate prominent theories, including *TAM* and its variants, into one unified model. This attempt to amalgamate tested theories, however, still does not apply in all settings, despite some attempts to extend key elements (Fuad & Hsu, 2018). While *UTAUT* holds the most promise for quantitatively investigating the adoption of learning analytics, it is unclear if it is useful from a qualitative end (Rempel & Mellinger, 2015; Williams, Rana, Dwivedi, & Lal, 2011).

Summary

In this chapter, I described the development of big data and learning analytics and shared ethical considerations around their use in educational settings. I then discussed key issues for adoption, such as public trust and data security, relevant learning analytics adoption studies, and the K-12 schools context. Finally, I concluded with prominent adoption theories and their applicability to this investigation. In the next chapter, I share the methodology for the dissertation.

Chapter Three

Methodology

The main goal of this study is to understand key factors that can promote and inhibit the decision to adopt learning analytics in K-12 schools. Doing so can contribute to building a foundation of literature to support K-12 leaders who want to use learning analytics and large-scale learning data. To achieve the goal of this dissertation, I conduct an exploratory qualitative research investigation. In this section, I introduce the research design, sites, participant selection, data analysis, and strategies to ensure trustworthiness of my interpretation. Finally, I discuss limitations with regard to the larger research project.

Research Questions

The following research questions guide this study:

1. How do psychosocial factors (perceptions, attitudes, and understanding) of K-12 campus and district leaders in North Texas promote or hinder the decision to adopt learning analytics tools and large-scale learning data?
2. How does internal (skills) and district (guidelines, training, support, technology and data infrastructure) capacity promote or hinder K-12 leaders' decision to adopt learning analytics in North Texas school districts?

Design

In order to address these research questions, I use a qualitative approach. Qualitative research, as described by Creswell & Poth (2017), is "sensitive to the people and places under study" and determines patterns or themes through both inductive and deductive reasoning (p. 8). It is also useful when a "complex, detailed understanding of the issue is needed" (p. 46). Since this is exploratory research of a complex phenomenon, this approach makes sense over a quantitative one.

I conduct semi-structured interviews with leaders in North Texas public schools and educational service centers in order to determine knowledge, skills, and attributes that might promote or inhibit adoption. This approach allows for a depth of response that includes describing experiences and providing specific examples to understand the process of change in the participants' contexts (Rubin & Rubin, 2005). It also promotes flexibility, so that the researcher can probe or ask follow-up questions, as needed, to explore topics in greater depth (Bernard, 2013). I identify participants through my personal networks and follow using *snowball sampling*, where participants identify others that have knowledge about the phenomenon under investigation (Creswell & Poth, 2017). I conduct interviews until I have reached emergent category *saturation*, when additional interviews do not meaningfully contribute to the study (Charmaz, 2014).

The SHEILA project helped to guide the direction of this study and I adapt my interview protocol from their investigation (Tsai et al., 2018). Their protocol included two different tracks that started with one filtering question which asked if the participants had a learning analytics project. If they answered yes, they completed Part A, and if they answered no, then they completed Part B. Part A focused more on adoptions and implementations that have taken place, where Part B looked more at readiness for adoption. Through the results of my pilot research, Part B is more indicative of the K-12 landscape in the region of study, so I choose to primarily utilize those questions. I summarize overlap between prompts and questions in Table 3.1.

Table 3.1

SHEILA Project and Dissertation Interview Protocol Comparison

Question/Prompt	SHEILA	Dissertation	Comments for Adapted Parts
2. Student data collection – type, storage, framework, vendors	X	X	Integrated with #3/4 and moved vendors into its own question
3. Reason for collecting data	X	X	Integrated with #2
4. Strategy for collecting data	X	X	Integrated with #2 and asked if publically posted
5. If yes, how implemented	X		Changed to focus on a hypothetical learning analytics adoption process
6. Ethical/privacy considerations	X	X	Asked for examples from their district
7. Usefulness of learning analytics in their institution	X	X	
8. Barriers to adoption	X	X	
9. Capacity and needed changes for adoption	X	X	
10. Essential components for learning analytics policy	X		After discussion with various researchers and K-12 leaders, I do not feel that many could answer it well.

After consolidating and removing some questions, I expand and add others that made sense for potential K-12 learning analytics adopters based on my pilot study. Given the growth of educational technology in schools, one question solely focuses on the district-vendor relationships (Cavanagh, 2014; Levin, 2016). Another factor that is especially relevant to this dissertation is understanding how districts currently adopt technology. Finally, it is useful to know how K-12 leaders seek to inform themselves about new technologies, including learning analytics. The interview protocol is available in Appendix A.

Based on pilot work completed in my Advanced Qualitative Methods doctoral course, I determine that each interview session would take between 30-60 minutes. Interviews take place in the school districts or via web conferencing tool and I record and pay for the electronic transcription of all sessions. Doing so can help me better and more quickly analyze the significant volume of collected data. I also ask for or provide a pseudonym for each participant to help maintain anonymity in human subjects research. Finally, I write memos for each interview at the conclusion of each interview and collect any district resources that may pertain to this study, including online policy manuals on district websites (e.g., "Richardson ISD board policy manual," 2018).

Research Sites

Each participant in my first study works in either a rural, suburban, or urban public school district around the Dallas-Fort Worth metroplex in North Texas or the Region 10 or 11 Education Service Centers. All of the districts in this study fall under these centers, which are support organizations that provide assistance to Texas schools, and encompass a broad range of student demographic factors, such as socioeconomic status, ethnicity, district size, advanced preparation, and college readiness (ESC Region 10, 2017; ESC Region 11, 2017). By sampling from a variety of schools in the North Texas region, I have a diverse pool of educators from which to draw. Creswell and Poth (2017) state that this approach "increases the likelihood that the findings reflect differences or different perspectives – an ideal in qualitative research" (p. 158). These locations are de-identified in the study findings to protect participants and are reported by size and type.

Research Participants

I use purposeful sampling, which include "a group of people that can best inform the researcher about the research problem under examination" (Creswell & Poth, 2017). First, I target both campus and district leaders in K-12 schools in North Texas. I invite these administrators to participate in this dissertation study to better understand different perspectives and investigate possible disconnect between levels in organizations (Cho & Wayman, 2014; Honig & Venkateswaran, 2012; Wayman, Cho, Jimerson, & Spikes, 2012). Although there are many stakeholders in the learning analytics adoption process, administrators play a more significant role as *change agents*, those that can influence other opinion leaders (Infante, Rancer, & Womack, 1997; Rogers, 2003), given their decision-making responsibilities (Ash, 2014; Maxwell, Locke, & Scheurich, 2013; Msila, 2011). Future inquiry with other stakeholder groups can add more to the overall picture of a complex process, but I do not include it at this time as it would drastically broaden the scope of the work.

In each region, I have a large pool of potential participants for recruitment. For example, during the 2016-2017 school year, the Region 10 Educational Service Center served 3,148 campus administrators and 1,267 central administrators (ESC Region 10, 2017). I work with each selected school district's Institutional Review Board procedures as needed and remain sensitive to solicitation concerns. Most leaders are relatively easy to contact via email, typically publicly available through campus and district websites or through central office electronic mailing lists.

In addition to these leaders, I contact employees at the regional service centers. These employees have typically served as K-12 leaders and help support a wide variety of districts in their current positions. For the purposes of this study, I seek out those who work with learning data, instructional technology, and curriculum, as they are likely to have the most experience related to the topic of this investigation.

In total, I interview 14 participants. Four are from educational service centers and 10 from public school districts, with five of those on campus and five in the central office. Campus leaders include elementary, junior high, and high school assistant principals and principals. Central office administrators comprise of a superintendent, assistant superintendent, curriculum coordinator, executive director of accountability, and senior director of technology. The educational service center positions all focus on different areas data and technology. There are seven males and seven females in this sample. Although my recruitment involved a diverse set of contacts, the final group that agreed to participate includes 12 White and two Hispanic leaders.

Data Collection and Analysis

In this study, I primarily collect data through semi-structured interviews and writing memos. I also explore the school district websites of interview participants to determine if there are any publicly posted guidelines and policies around learning data and technology. All interviews occur face-to-face or via web conferencing tool and take up to one hour to complete, making use of the approved protocol (*Appendix A*). Immediately following each interview, I write memos about how each session went and any observations that I made (e.g., participant reactions or body language, condition of facilities).

After recording and transcribing each interview, I remove any identifiers to protect the identity of the participants and send the cleaned transcript to the participant for further review with their pseudonyms. All transcripts and memos are stored digitally on an encrypted, password-protected computer and backed up using cloud-based system that is approved by the university's institutional review board. I will store data for a minimum of three years after the end of study in accordance with the university's retention policy.

I systematically review and analyze all data collected during the interviews using coding methods recommended by Charmaz (2014) and Saldaña (2016). This process includes memo writing, line-by-line coding, axial coding, and transforming data into emergent themes. I outline each of the following steps below.

Memo Writing

Memo writing is an important part of the qualitative research process as a mechanism to move beyond descriptive notes to analysis (Saldaña & Omasta, 2018). These memos are reflective in nature and provide a space to ponder participant reactions, identify emerging themes, share challenges, and more (p. 54). I store my memos along with the transcripts and read them multiple times throughout the study in order to build and iterate. Chamaz (2014) states that emergent analysis is ultimately shaped and formed through memos and bringing data into the memos helps to ground them while improving their analytic capability and promoting abstract thoughts (p. 182).

Line-by-Line Coding

I conduct initial line-by-line coding of each transcript that includes close reading while remaining "open to all theoretical directions" (Charmaz, 2014, p. 114). This process includes literally reading each line of text as opposed to "sentence-by-sentence or even paragraph-by-paragraph coding is permissible" (Saldaña, 2016, p. 117). Doing so "encourages active engagement with data" (Charmaz, 2014, p. 343) and leads to the creation of an index of codes.

Axial Coding

Next, I use axial coding to find relationships in the index and pull out emerging axis categories, which others revolve around (Saldaña, 2016). Whereby the initial coding breaks data apart, this step brings it back together in an organized, coherent manner (Charmaz, 2014). Given that I have 14 participants, this step is extremely important to fit their perspectives into the larger story by helping reduce the total number of codes by collapsing them and finding common connections.

Emergent Themes

I use the *constant comparative method* where I continue to iterate categories by comparing them with data from each subsequent interview, including memos and other collected sources. The goal is to eventually reach saturation, where nothing is added to the data by collecting more of it (Creswell & Poth, 2017). Themes emerge through analysis of all of the data and serve as the investigators interpretation of what participants shared. These themes are reported in the findings as insights into the experience of the people under investigation and the beginning for potential theories.

Trustworthiness

In order to improve the trustworthiness of my interpretations, I employ three strategies outlined by Creswell and Poth (2017). The authors suggest that "qualitative researchers engage in *at least two*" of these strategies (p. 258). The following strategies are in no particular order, but serve to enhance the quality of this study.

Clarifying Researcher Bias

In Chapter 1, I included a section titled Personal Relevance where I shared my background and experiences with K-12 and learning analytics. By doing so, I acknowledged any potential bias that I might have due to being close to the subject under investigation. This could help to illuminate potential issues with my interpretations.

First, I shared that I worked as a junior high teacher and coach at a visual arts and technology magnet in a North Texas school district for four years. The campus had a culture of success as a high-performing Title I school. While I left full-time teaching to pursue a graduate degree, I continued teaching there as a substitute and was the primary social studies tutor for at-risk students. I remained in higher education, but continue to maintain an interest in K-12.

At my university, I have worked for one of the preeminent learning analytics scholars and have gained exposure to the field in my job. During that time, I have built my own global network on five continents and actively participate in the Society for Learning Analytics Research (SoLAR). I have attended and presented in the last five conferences and SoLAR funded me to participate in the learning analytics summer institute that meets each June and a doctoral consortium at the annual conference. In my position, I helped to develop a massive open online learning course series in edX and a learning analytics master's program at my university. I originally focused on ethics and privacy in learning analytics *big data* when I began my doctoral studies, but became more interested in the adoption process and how to build capacity through my communication with other scholars and attendance at events.

Member Checking

After transcribing and de-identifying all interviews, I share the transcripts with the participants. At that time, they may further redact, clarify, or add any information. Upon completion of the main findings, I share them with participants for additional feedback. This step is considered by some to be "the most critical technique for establishing credibility" (Creswell & Poth, 2017; Lincoln & Guba, 1985).

Rich, Thick Description

I designed my interview questions to encourage great quantities of detail and provide examples specific to their context. By doing so, it may be possible for readers to "transfer information to other settings" through "shared characteristics" (Creswell & Poth, 2017, p. 263). This includes the interconnectivity of different details.

Limitations

As described in Chapter 1, there are a number of limitations in this study. First, there is little research on the use of learning analytics, which limits my ability to situate this study in the current literature. By using an exploratory research design, I will provide an early contribution to the field. Second, this study focuses solely on leadership positions and excludes other stakeholder groups. Since leaders are the primary decision-makers for the adoption process, this population makes sense for this study, but I argue that future studies should include other stakeholders. Finally, participants were more difficult to attain than anticipated due to district research review boards. This mechanism increased the time needed to complete the study and also led to changing previously targeted districts due to requested changes that would fundamentally alter the research investigation. It may have also potentially limited the diversity of participants in this study.

Summary

In this section, I introduce the research design, sites, participant selection, data collection and analysis, strategies to ensure trustworthiness, and limitations of this qualitative study. I also share the influence of the SHEILA project on the interview questions and how I modify them to fit the North Texas K-12 context. In the next chapter, I report on the results from my analysis and finish with a discussion of the findings and their implications for future research.

Chapter Four

Findings

The main purpose of this study is to understand what might promote and inhibit the decision to adopt learning analytics in K-12 public schools. Due to the limited amount of relevant research concerning this topic, I conducted an exploratory qualitative research investigation to address this gap in the literature. To do so, I interviewed participants working in North Texas public schools and gather information about their contexts, such as location, size, and staffing. In this section, I introduce the participants and then share findings from my data analysis. I present these findings as themes that emerged while exploring both research questions.

Participants

I recruited participants using purposeful and snowball sampling in order to better understand the research question and finished with 14 total. Each of the participants works in an educational service center, campus, or district in Regions 10 or 11 in North Texas and has had a leadership role. There is a balance of seven males and seven females; however, despite intentions of having greater racial balance and approaching a diverse set of contacts, the overwhelming majority of people that agreed to participate were White (12) with two Hispanic interviewees. Each participant has an assigned pseudonym that was chosen by the subjects or the researcher to preserve anonymity to the greatest possible extent.

In order to better profile participants, I asked each to disclose some demographic information. These items include sex, race/ethnicity, birth year, highest degree attained, discipline, and years working in K-12. I combined the data with job titles and district characteristics (such as size and location) to complete the overall picture of the participants. The rationale for collecting this data was to determine possible similarities and differences that might arise in each category. Additionally, I asked about their own perceived innovativeness and attitude toward new technology, ranging from 1 (focused on traditions, risk adverse, late to adopt new technologies) to 5 (innovative, takes risks, quick to adopt new technologies).

Ashley

Ashley is a White female in her 40s. She has worked for over six years in an educational service center as a consultant and has 17 years' experience as an educator. This includes time in the central office as an intervention and professional development coordinator. Ashley has a doctorate and rates her attitude toward technology as a 5, seeing herself as very innovative, willing to take risks, and quick to adopt new technologies.

Robin

Robin is a White male in his 60s. He has worked for 31 years in an educational service center, currently in a leadership role, and has 39 years' experience as an educator. This includes time as a campus principal. Robin has a master's degree and rates his attitude toward technology as a 5, seeing himself as very innovative, willing to take risks, and quick to adopt new technologies.

Michael

Michael is a White and American Indian male in his 40s. He has worked for five years in a small, rural school district that is predominantly White. He has 22 years' experience as an educator and currently serves as district superintendent. Michael has a master's degree and rates his attitude toward technology as a 3, seeing himself as neutral in terms of being innovative, willing to take risks, and quick to adopt new technologies, which he primarily attributes to cost and budgetary reasons.

Bradley

Bradley is a White male in his 50s. He has worked for five years in a large, urban school district that has a very diverse student population. He has 27 years' experience as an educator and currently serves as an assistant superintendent. Bradley has a doctorate and rates his attitude toward technology as a 3, seeing himself as neutral in terms of being innovative, willing to take risks, and quick to adopt new technologies

Paul

Paul is a White male in his 40s. He has worked for two years in a small, rural school district that is predominantly White and Hispanic. He has 21 years' experience as an educator and currently serves as a high school principal. Paul has a master's degree and rates his attitude toward technology as a 4, seeing himself as relatively innovative, willing to take risks, and quick to adopt new technologies.

Pearl

Pearl is a White female in her 50s. She has worked for two years in an educational service center as a consultant and has 10 years' experience as an educator. This includes a curriculum development role. Pearl has a doctorate and rates her attitude toward technology as a 3, seeing herself as neutral in terms of being innovative, willing to take risks, and quick to adopt new technologies.

Natalie

Natalie is a White female in her 40s. She has worked for four years in an educational service center as a consultant and has 22 years' experience as an educator. This includes time in the central office as an analyst and professional development coordinator. Natalie has a master's degree and rates her attitude toward technology as a 4, seeing herself as relatively innovative, willing to take risks, and quick to adopt new technologies.

James

James is a White male in his 50s. He has worked for 17 years in a small, suburban school district that is predominantly Hispanic and African American. He has 23 years' experience as an educator and currently serves as a high school assistant principal. James has a doctorate and rates his attitude toward technology as a 4, seeing himself as relatively innovative, willing to take risks, and quick to adopt new technologies.

Erin

Erin is a White female in her 30s. She has worked for 11 years in a small, rural school district that has a very diverse student population. She has 18 years' experience as an educator and currently serves as district curriculum coordinator. Erin has a master's degree and rates her attitude toward technology as a 5, seeing herself as very innovative, willing to take risks, and quick to adopt new technologies.

Isaac

Isaac is a Hispanic male in his 40s. He has worked for 17 years in a large, suburban school district that has a very diverse student population. He has only worked as an educator in this district and currently leads accountability efforts in the central office. Isaac has a master's degree and rates his attitude toward technology as a 5, seeing himself as very innovative, willing to take risks, and quick to adopt new technologies.

Laurie

Laurie is a White female in her 30s. She has worked for three years in a large, urban district that has a very diverse student population. She has 11 years' experience as an educator and currently serves as an elementary school principal. Laurie has a master's degree and rates her attitude toward technology as a 5, seeing herself as very innovative, willing to take risks, and quick to adopt new technologies.

Britanny

Britanny is a White female in her 50s. She has worked for 19 years in a large, urban school district that has a very diverse student population. She has 29 years' experience as an educator and currently serves as an elementary school assistant principal. Britanny has a master's degree and rates her attitude toward technology as a 3, seeing herself as neutral in terms of being innovative, willing to take risks, and quick to adopt new technologies.

Jim

Jim is a White male in his 40s. He has worked for six years in a large, suburban district that is predominately White. He has 27 years' experience as an educator and currently leads technology operations in his district. Jim has a master's degree and rates his attitude toward technology as a 4, seeing himself as relatively innovative, willing to take risks, and quick to adopt new technologies.

Michaela

Michaela is a Hispanic female in her 40s. She has worked for six years in a large, urban district that has a very diverse student population. She has 22 years' experience as an educator and currently serves as a junior high school principal. Michaela has a master's degree and rates her attitude toward technology as a 4, seeing herself as relatively innovative, willing to take risks, and quick to adopt new technologies.

Participant Summary

Overall, the participants have diverse backgrounds and unique experiences, but all have served in a leadership capacity in K-12 public schools. Their age range spans from 30s to 60s and all have at least 10 years of experience as an educator. All of the participants rate their attitude toward technology from three to five, with none having a strong, negative view. In the next section, I share the results of my thematic analysis.

Thematic Analysis

During my analysis of the interview data, I used the adapted Multicultural Competency framework to identify major categories that helped to answer my research questions. Upon approaching saturation, three major themes emerged from the analysis: (a) knowledge, (b) perceptions and attitudes, and (c) capacity. Throughout the remainder of this chapter, I will share these and finding and their corresponding subthemes.

Knowledge

The first theme that emerged is knowledge, which addresses the first research question about psychosocial factors that promote or inhibit the adoption of large-scale learning data and analytics. Two key subthemes emerged under knowledge. First, K-12 leaders' understanding of learning analytics and data varies. Second, leaders inform themselves about new innovations and trends, such as learning analytics, in many different ways. I share these findings in the following sections.

Understanding of learning analytics and data varies. During the interviews, I directly asked each participant to define learning analytics. While the responses varied greatly in understanding, which tended to cluster between campus, central office, and educational service centers. I present the findings in that order.

Campus leaders had a wide range of responses. Paul, a high school principal, remarked that "when I think analytics, I think Moneyball. You don't have to have… a superstar in every position… you look for tendencies and kind of a fit for what people do well… and play in the percentages." Britanny, an elementary assistant principal, felt it was taking all of their data and using it to analyze learning and instruction. She remarked that "analytics is analyzing, and analyzing, and analyzing," noting the amount of effort needed to do so. Laurie, an elementary school principal, shared that she had never heard the term before. She thought that learning analytics is analyzing data to drive what happens during the learning. Laurie felt that the reason educators need to be "data-focused or data-driven is because there's the hope is that there's a change in the instruction." Michaela, a junior high school principal, had also never heard the term before. She defined it as "looking at data to help us inform us on instruction. Where are we going with regards to instruction, with support for kids, with support for staff, with support for our community? What is the data showing us?" She continued that it could also include looking for trends to inform educators to make better decisions. James, a high school assistant principal, mentioned that it was more data to help understand how students learn, comprehend, and retain. He stressed not simply looking at descriptive data, but thinking about how the data could help design what educators do with students. In summary, these five administrators had little experience with the field of learning analytics and a number had never heard the term prior to the interview. They generally define it around analysis of learning data to improve instruction.

Next, I describe central office leaders. Jim, who helps direct technology operations at the district level shares that learning analytics can help make data more actionable in real-time. He states that "we don't want an autopsy report. We want to get the data ahead of time." He feels that if his office can get that data ahead of time, and his goal would be to crunch the numbers literally for the next day. Jim continues that this can be extremely important in subjects like mathematics, which build heavily from lesson to lesson. Isaac, who leads accountability efforts at the district level, saw the importance of predictive measures to identify possible gaps and getting away from snapshots. He also stressed the ability to make “learning responsive to what their individual needs are… using the information to guide instruction and intervention, but through various outcomes and checkpoints throughout the year.” Isaac feels that learning analytics are important for the K-12 space because of the amount of tasks that teachers and students have to do. He believes that his district needs to be using the information to help streamline those processes so that they have more time to spend on the areas that they need in a smarter way. This is similar to what Paul mentioned, but being more efficient and focusing on gaps. Erin, a district curriculum coordinator, believes that learning analytics should measure specific learning targets and that it makes her think of personalized learning, which she describes as “knowing where each student is and where they're at and with what they need next.” As a senior leader, Bradley stresses that learning analytics can help with driving data down into the classroom so that teachers can make day-to-day adjustments. He also mentioned giving immediate feedback to the students, so that they can make immediate improvements. Michael, a superintendent, similarly saw learning analytics from the data perspective, where someone pulls data and puts pieces together for them. He also stressed the he wanted that person to explain it to then in a way that they would all be able to “get out there and use it quickly.” The central office leadership, while recognizing the need make changes in the classroom, focus more on making use of data in real-time or as close as possible. This can aid with personalization and individualized instruction, better predicting future outcomes, and gap identification.

At the service center, Ashley stresses that there is a difference between data analytics and learning analytics and what they are measuring. She has concerns that if districts do not have a battery of instruments to collect data, “you run the risk of kind of making some assumptions just based on one type of data point. And that can be dangerous.” Ashley finishes by remarking that districts that do well with learning analytics are probably the ones that have multiple measures and have developed a system to get as many different kinds of data points as they can. Pearl furthers this idea, saying that “you're taking data, all different kinds of data, related to learning outcomes. When I say outcomes, learning processes, learning outcomes, and looking for patterns, looking for trends, looking for maybe the why, the how.” Robin feels that learning analytics will not be used well given the data that districts focus on presently. For Robin:

> *What I see collected is primarily either state assessment data, or benchmark data related to state assessment data… But for the most part-- you're talking about learning and data-- people struggle to get beyond something that's easily measurable. And so it tends to be some kind of test scores… Since they're not easily measurable, they're typically not included in any kind of accountability systems. And if they're not in the accountability system, they don't get a lot of traction unless they really tie-in with a district who has a strong strategic plan and follows that process, and it fits within what they're trying to do… We tend to measure the things that we can quantify. And what we can quantify are test scores… And that's what most learning analytics tools are designed to help you improve. And those aren't necessarily the things, I think, that help kids learn.*

Natalie similarly stresses that learning analytics means looking at the right data to determine if learning has taken place. The leaders at the educational service centers have a bit more critical perspective about learning analytics. This includes increasing the amount of data used in analyses and ensuring that it is the best data for it. Like Michaela, trend identification also could play a role by looking at larger issues through additional datasets that did not previously exist.

In summary, campus leaders saw the value of learning analytics for improving instruction in general, district-level leaders recognized the need to expedite the movement of data into the classroom to improve student outcomes, and service center leaders stressed collecting more data and identifying what should be used for analysis. Campus administrators had less knowledge about learning analytics than central office or service center leaders. In the next section, I share how leaders choose to learn more about new approaches, like learning analytics.

Inform themselves in different ways. K-12 leaders make use of a myriad of different methods to inform themselves of educational innovations and current trends. All participants reported that they had at least one way they kept current, while some made use of many. For example, Jim mentioned reading blogs, vendor pages, educational white papers, and Twitter as well as attending conferences. Robin prefers media sources like EdSurge while Laurie likes attending online webinars and educational technology conferences like the International Society for Technology in Education (ISTE). Britanny primarily uses a search engine because she could find content in “layman’s terms.” Only one participant stated that they read academic research journals for information on innovations and trends.

Personal connections with others in their districts or neighboring districts, as well as educational service centers, were the primary sources for Michael and Erin. Michael shared his experience at superintendent meetings that occur throughout the year. He stated that:

> *Different superintendents stand up and talk, and their curriculum people will talk about something that's-- something that they feel like is worthy of everybody knowing about, that kind of thing. So I hear I hear a lot of things through that. And then we have a lot of meetings whenever they've gotten to the point where they've seen those two or three companies that they really like.*

Erin tends to lean more on the technology people in her district office and the educational service centers for their expertise, particularly for technical items. She does not directly communicate with vendors, stating “I feel like a lot of times they're sharks” and “as soon as you contact them, they just never leave you alone.” She feels that she is constantly flooded with emails from them. Robin shared that he is also approached by a lot of technology vendors. However, he recognizes:

> *The idea of exponential change and educational technology. And you can't keep up with everything. You used to try to learn everything that came out, and know everything about everything. You can't do that. So you've got to be more aware of trends, and know how to find information about the things that you need to, and be willing to recognize when something presents itself that may be a little different or have some potential to be able and willing take a look at it. But I say all that-- I'm going around the bush here. Basically, I don't try to stay on top of every tool that comes along. And I've given myself that permission a long time ago.*

There are a plethora of resources available to educators who want to stay current on trends, ranging from simple searches, to media and published content, to attending events. People working in educational service centers or technology and data offices tend to explore more resources, while campus faculty and senior leadership focus on word-of-mouth and specific targets. Regarding learning analytics, much of the work done in the field has taken place in traditional academic journals, which are less accessible. The participant that mentioned these journals had a doctorate, which could be one reason for the awareness. Next, I share the findings for the second theme.

Perceptions and Attitudes

The second theme that emerged is perceptions and attitudes, which addresses the first research question about psychosocial factors that promote or inhibit the adoption of large-scale learning data and analytics. Two key subthemes emerged under perceptions and attitudes. First, K-12 leaders' are conflicted about the data that they currently have available. Second, leaders perceive a large number of challenges, opportunities, and concerns about the use of learning analytics. I share these findings in the following sections.

Conflicted about available data. As educators are increasingly required to use data to make decisions on public school campuses, some leaders are relatively positive about the process. For example, Laurie shared that before the students return from summer break, her teachers work half a day on a "data dig" where each teacher sees data for their upcoming learners. She continues, saying, "I don't think I know I couldn't make decisions for our campus if I didn't have that data because it's like a flashlight into what needs to happen [in] the classroom." Similarly, while Britanny feels like her district gives them a lot of data to work with. She calls herself a "number cruncher," but is sometimes shocked that her district keeps giving her more and more data to review. While she enjoys looking at numbers, she is sometimes overwhelmed by it

Others have a more negative perspective about the use of data. Natalie shared about a teacher expressing concerns that they don't have the time to review the data and make adjustments in the learning. Even worse, James remarks that overall "we use data as a threat and as a punitive tool and not as an opportunity to improve instruction." This applies to students, teachers, and administrators in his district.

Still others have mixed attitudes. Pearl feels that districts are pretty good at collecting data, but the challenge is "how do you turn it around quickly and use it now. Not next year, when we go, OK. Well, we should have done that. But right now." Michaela remarks that:

> *I really enjoy looking at data. I mean, it really helps us make decisions for our instruction. I wish that our data was easier to manage... But a lot of times, we kind of*

struggle with, where do we find this report, where do we find this report? And so I know that there are some programs out there that are very user friendly and we have access to data at our fingertips. Any data that you can give me that will help us move and help students, I welcome it… Having access to more data about time, engagement, and writing-- we would love that. Personally, I would want that… While I welcome the data, sometimes, it's a little overwhelming, because I'm trying to pull this report. So you have to go here to this hub. And for this report, you have to go here. And in this time and age, I wonder if there is something where we can just have one hub rather than the different ones. And we're kind of trying to search for different things in different places.

To her point, easy access to data dashboards that could pull specific reports would go a long way to meet her needs, rather than having to sift through many locations in isolated, unconnected systems.

Robin sees the value of data and learning analytics, but isn't fully convinced:

At some levels, it's a very drilled down, very granular look at both individual students and individual results for an individual student, looking at doing some kind of item analysis, in some cases getting as deep as looking at what distractors they chose versus correct answers, and trying to think of the reasoning why they would have chosen that kind of thing. So it can get to that specific level of granularity. That's pretty time intensive. And I'm not sure that it always contributes a whole lot to the overall picture of what kids need to learn, or probably need to learn.

Erin feels that data "gets us from point A to B" and that education, as a whole, is behind. In particular, she argues that data is really siloed, specifically at the secondary level. For her, elementary teachers who have 22-24 children all day long have a different set of problems than secondary. Potentially working to better integrate systems for a streamlined and time-efficient experience is a potential doorway into more meaningfully using data.

Overall, leaders are mixed about the use of data. Changing school district culture, promoting safety and trust, demonstrating improved outcomes, and easing the use might foster more positive attitudes towards it. In the next section, I discuss the different challenges, opportunities, and concerns that the participants had about the use of learning analytics.

Numerous challenges, opportunities, and concerns perceived. The K-12 leaders in this study shared three key areas that they perceived about the future use of learning analytics. The first area, challenges, includes data, vendor relationships, and school districts. The second area, opportunities, comprises of individual student contexts, quicker access to data, and better explanatory power. The final area, concerns, consists of data privacy and security, stakeholder awareness and ownership, responsible use of data and algorithms, and tool effectiveness and cost. I share these findings in the subsequent sections.

Challenges**.** The study participants as a whole identified a large number of challenges using learning analytics and large-scale learning data in their district. They can be condensed into three primary elements, including challenges around the data, vendor relationships, and the school districts. Some of findings can potentially fit across these elements, such as lack of statisticians.

Data. The first challenge identified is around data and comprises of items such as communication, making data actionable, and turning data around quickly. Jim, who has a data role in his district, has trouble discerning information about his own children on their reports. He feels that most school districts are lagging behind in that communication piece. This might include clear documentation about what the data means and includes in it.

Ashley argues that translating information into “actionable, productive, instructional practice changes is one of the biggest challenges for data. And that's not a new challenge.” She suggests that it is easy to become satisfied with large amounts of data, but will it change instructional practices or just try to go chase some content that did not score well? She describes the chasing as a “Band-Aid type fix” which is based on initial gut reactions from looking at spreadsheets or graphs, or even student profile data instead of asking tough questions about it.

Finally, Pearl shared that her time in the classroom was overwhelming with difficult expectations. In particular, there was a demand to turn data around quickly and cleanly. This ultimately led them to rely on test data, because it came through an educational data warehouse, which was easy to access and stored everything in one place.

Vendor relationships. The second challenge pertains to relationships with educational technology vendors and their products. Specifically, this includes quality, promises, and costs. Robin feels that there are a whole lot of the educational technology vendors are in the “data space, data analysis, data collection, data synthesis, data this, data that. A lot of those folks are solutions in search of a problem.” His main concern is that they promise what they cannot deliver in order to sell a product. In a similar vein, Erin remarks that:

> *They're really flashy. And they promise the moon. And a lot of times when I get into actual looking at what data it produces, or stuff like that, it's a lot of data solutions. A lot of oh, we can save you time… There's just so many different products out there. They all seem to be trying to vie for different things. And they're all selling their product as the best. And we've had several of them, and none of them have really wowed us. And our students don't like them.*

Even with the negative perception, Robin feels that vendors in this space want what is best for students and to address a school district's needs. However, he continues that some of them do it better than others. He is mostly concerned about the level of prediction promised and is not "aware of any that have really cracked that nut." Natalie also shared a positive relationship with vendors. She feels that "they're all very passionate about the product and believe in their product, and feel that their product is the one that can help change, or make change within, the district." However, this does not mean that their products are always the best fit in specific contexts.

Erin identified another significant challenge to using educational technology: cost. She shared that to really implement full-scale learning analytics, they do not have a device for every single student simultaneously, which is another barrier for them. Financially we can't afford it. She continued that they "maybe could do a bond and afford the upfront cost. But then the aging technology and replacement cost is not something we can sustain." One-to-one computers can be quite expensive, as can other technology infrastructure and security costs. This also diminishes risk-taking and innovation and Michael notes that districts "just can't afford to do everything." Ultimately, they have to pick and choose what they can do.

School districts. Each school district has its own unique context and corresponding challenges. Bradley mentions that he works in a large district and that new implementations are a challenge to do well. He feels that there is always work to do there. Within a district, Isaac highlights that "every campus is different…. has a different culture, and it's going to use things differently." He recognizes that each campus has different levels of capacity based on their teachers and different levels of need based on their students. Given the variety of campus contexts, Natalie remarks that a lot of pressure to use data is to improve test scores and get a good state rating. Getting a high rating takes some of the pressure off on campuses and potentially a district at large.

James shares the inability for his district to make many gains, partially due to systemic reasons. He notes that:

> *Being a high-poverty district, we can't rely on the community support or family support. I know that the community and family want to support. But in the environment and the community we live in, that's not as reliable as we would like. So we do a continuous and ongoing amount of collection so that we can track kids and not let them fall behind… We go microscopic to try to find where the gap widened instead of saying, you know what? Let's follow the schedule and see if they rebound. We automatically assume they're not going to rebound, and we add in more assessments to stay more on top of their performance, which of course becomes a vicious cycle, because the kids hate the additional assessments, so they don't really perform, which means that their performance goes down, which means we do more assessments, which means that they get sick of that again. You see how it just erodes in on itself…. We haven't embraced formative to the point where we are using it like we are the summative. And a lot of that's because I get the sense that our district doesn't trust teachers to have a good handle on how to do formative assessments.*

This disparity contrasts with Jim’s situation, where he feels that we are in a time in education where we can have deep data on every single student and each of them can have an individual path. There is continued difficulty innovating given current policies and funding structures and he remarks that they “just don't have the skills to implement it.” Robin furthers this by stating that most districts do not have strong statisticians. In those cases, he shares that a superintendent or principal, typically “puts stuff on a spreadsheet and just looks at it, and tries to make sense of it.” Michaela goes one step further by highlighting high teacher turnover. When someone new comes in, the campus has to train them. What was more frustrating is that "once we train them, then the system changes. So now we have to retrain." This puts a lot of pressure on campus administrators to have consistency and improve outcomes for their students.

Even when a district invests in a new, expensive learning platform, it is not guaranteed to succeed. James recounts his experience with platform that had only been in place for one year before they abandoned it. What frustrated James is that "none of that data for time on task or engagement was ever released to any of the leadership. I would love to be able to see information like that." He continues by remarking that "it's like we went out and bought the race car and never took it to the racetrack." Part of the reason why adoptions fail is because of a constant stream of trying new things, rather than picking something and sticking with it. Erin said, "we just have so many new initiatives that we constantly are rolling out that our teachers, they experienced implementation fatigue… they're compliant, they'll do it. But are they utilizing it to the best of its ability?" Although it is reasonable to move away from ineffective products, rather than continuing to pay for something inferior, but more effective systems are also abandoned in favor of new ones.

Another challenge that that educators do not typically have enough time to do everything that they need to do, much less and new tasks on their plates. Laurie, an elementary principal, feels that elementary school "teachers are around 22 kids all day long teaching their hearts out. They also don't have time to then pull 1,000 data points." Britanny furthers this by sharing the following:

> *I think time for analyzing-- a lack of time for analyzing. Our teachers get 45 minutes a day of conference planning, which… It's not a lot in the big picture of things. We're asking them to do lesson plans, and have parent conferences, and 504 meetings, and*

ARD meetings, and go to the bathroom… And I think that amount of time that they're given just to sit and analyze is not enough because if you really do a good job of it, 45 minutes a day doesn't cut it.

Therefore, in order for school districts to make use of large-scale learning data and analytics, there likely needs to be a corresponding increase in time for faculty to improve their skills and work with the information.

In short, three subthemes emerged during analysis of challenges. These include data, vendor relationships, and school districts. In the next section, I highlight key opportunities identified by participants.

***Opportunities*.** During the interview process, participants described a number of important opportunities when using large-scale learning data and analytics. The opportunities collapse into three elements. These include greater focus on the individual student context, quick access to greater amounts of data, and better explanatory power than currently available.

Individual student context. For the individual student context, there are a number of key elements. First, is the notion of personalization, shared by a number of participants. Erin stressed that in her district, they want to personalize learning for every single student. Along similar lines, Jim mentioned that "we always talk about, every kid needs something different. For the first time ever, that's a true possibility."

Second, participants highlighted the potential for students to have greater control by empowering them with data. Paul shared that "anytime a student can take ownership of their own learning, that's going to be huge for us." Britanny reinforced that idea, stressing that getting to the point where it is user friendly enough for the learners to take ownership of their own learning would be amazing.

Third, there is more potential to integrate data in such a way that can paint a more complete picture of students for administrators. For Ashley:

> *I do think that there is a trend to start looking more holistically at that sort of stuff too. I know in the department that we're in, we're always being asked, or kind from for those data warehouse sorts of things that pull in maybe your student information system attendance and behavior data and academic achievement data, and things like that, so that they can really build a more robust profile of a student. I think that's a lot more helpful probably at the principal and above level. I think teachers pretty much know when their kids aren't there, that they're not learning. You know, they can sort of paint that picture for you. But I think for principals, it's hard for them to see the picture of students, especially in large high schools and things like that.*

While Ashley specifically focuses on helping leaders, it is also worth mentioning that the data can also support teachers in the learning process, particularly at the secondary level where one might have 150 students.

Quicker access to more data. Besides more personalization, empowerment, and holistic views for students, interviewees also stressed that the access to more data that is at the educator’s fingertips hold great potential to develop real-time, actionable interventions. Isaac expressed that desire to get all the way down to the student level to have conversations in the classroom. He stressed getting data down quickly so that it could make an impact. Laurie, as a principal, also needs data readily available and the prospect of having more disaggregated data is exciting for her. At present, this is very difficult for them to attain.

Better explanatory power. Finally, K-12 leaders feel that learning analytics have the potential to provide more explanatory power than current methods. Michael, a superintendent, feels that:

> *You know, I think we test too much, I'm just going to say that. We do test a lot. I'm going to probably sound a little crazy here, but I really don't think the standardized testing piece is as important as some of what [we're] talking about here. The state's spending these massive amounts of money for standardized testing to where these kind of programs, if designed right, I think could be a more efficient way to do that.*

Bradley, an assistant superintendent, while thinking about the current system as it is currently constituted, feels that schools can reduce the variation in the amount of achievement that students are making. Whether overhauling current structures or continuing as status quo, both senior leaders recognize the potential for learning analytics to make an impact on student learning outcomes.

In summary, three main subthemes emerged for opportunities for learning analytics and large-scale learning data. The granularity and combination of data can promote greater personalization and understanding of individual contexts. Great access to deep data and easy access through dashboards and other mediums can help with the creation of real- or near-time, actionable steps to improve student learning. Learning analytics can also provide greater explanatory power if used well and can potentially shake the foundations of how we measure student achievement. Next, I share concerns that leaders had about using learning analytics.

***Concerns*.** While participants discussed a number of different concerns around the use of learning analytics and large-scale learning data in schools, four main elements arose during analysis. These concerns include data security and privacy, stakeholder awareness and ownership, responsible use of data and algorithms, and tool effectiveness and cost. Each concern has two parts given the overlap of the ideas.

Data security and privacy. Data beaches were one of the most common concerns shared by participants. Michael discussed a data breach at the Texas Association of School Boards that compromised employee information. While her district had not experienced one, Erin shared about internal conversations about Google Education's analytics and what it was collecting about children. She expressed skepticism, saying that "they've come back and said that they're not. But you know… that's for the bigger powers that be to work those things out." For Erin, there is a lot of trust and good faith that technology companies will do what they say they're going to do. Laurie and Britanny both highlighted data privacy of students as a key issue with the growth of technology and increasing use of data.

Stakeholder awareness and ownership. Stakeholder awareness and ownership is the second key concern. Ashley asked if students, teachers, parents know that information is being collected and how transparent districts are about what data is collected and shared. Additionally, Robin asked, "does that data belong to the district? Does it belong to the student? Should the parents have control of that data, and determine what's shared with the district and what's not shared with the district?" His main concerns was that he felt that those decisions are typically made with the best interests of the system and not always with the best interests of the individual. The main argument for the collection of this data is fiduciary responsibility of a district to use whatever resources it has to increase student outcomes and reach key metrics, such as graduation.

Responsible use of data and algorithms. Next, Bradley feels that the biggest ethical dilemma is the appropriate use of data, which has become a king commodity. Individual information is constantly shared across the internet without knowledge. In an educational context, data can have a major impact on student success. It can directly influence promotion, the provision of resources, and in an analytics context, recommended interventions. Pearl fears that "we're wandering back into that sort of labeling of have I doomed you to fail because the predictive analytics model suggested you might be this, and now in my mind, you are this." She also suggests that the models depend on who uses them and how they use them. Isaac also stresses the need to make "sure that we're not using the information to pigeonhole a student into a certain area or a certain framework." Moreover, Isaac warned about not using the information to punish teachers. His main concern is that most data are snapshots and context is difficult to glean. For example, if there is "a teacher that's having a bad day, kids that are having a bad day, those types of things… [it's important to make] sure that you're also not using the data against your own staff." He has a well-founded concern about the high-stakes nature of education and the propensity to use data for punishment over opportunities to grow.

Tool effectiveness and cost. Finally, solutions offered by third-party vendors can overpromise and underdeliver, and come at great cost. James shared an anecdote from his district about his experience:

> *They promise individualization. They promise that we're going to see our kids improve using their product. But we stay within the same three or four percentage points across the board year after year. And I'm willing to bet that that's the same state wide. And you may move up incrementally four or five points a year, but I'm not sure I'm hearing about districts that are able to move 18 to 25 percentage points by using it.*

For James, there is a serious question as to whether it is worth the investment in new technology, such as learning analytics, for meager gains at best. Ashley also recognizes a significant challenge that getting systems that provide good, usable data are incredibly expensive, which is a challenge for districts that have limited resources. Cost and/or having been burned by a previous experience that went poorly could a natural hesitation to use something like a learning analytics solution through a vendor.

Overall, these four areas of concern were not significant enough to dissuade participants from the idea of using learning analytics. However, they pose important questions that do not have easy answers. Developing a framework for the adoption of learning analytics in K-12 public schools should consider concerns such as these in order to promote buy-in and improve the success of an implementation. In the last section, I share findings from the final theme.

Capacity

The final theme that emerged is capacity, which addresses the second research question about internal and external capacities that promote or inhibit the adoption of large-scale learning data and analytics. Three key subthemes emerged under capacity. The first subtheme is about North Texas public school district mechanisms and infrastructure for learning analytics adoption. Second, leaders have greater technology literacy than data literacy. Finally, there are significant disparities between small, rural and large, suburban and urban school districts. I discuss these subthemes in the remaining sections.

District mechanisms and infrastructure for adoption. K-12 public schools in the Regions 10 and 11 service areas generally have systems in place to help with the adoption of technologies, textbooks, curriculum, and more. All of the participants shared that school districts typically make use of a committee of different stakeholders in order to vet and make recommendations for procurement. No districts sampled publicly shared information on this process; rather, this was communicated internally. Michael mentioned substantial investment in new computers, all two or fewer years old, and Isaac stated that “we've got a pretty diverse ecosystem of hardware in the district that's being used for instruction in multiple ways.” Laurie said that her district had so many technology options, it almost felt like “you could spend $1,000 every day on a new program-- a new technology program that's the latest and greatest.” These technologies are key to the data collection needed to make use of learning analytics. Sometimes the technologies themselves offer learning analytics solutions.

When making these types of decisions, Bradley said that:

> *There are times when we identify need. And then we go seek out a vendor. And that's a different process. So typically if we identified a need ourselves, then we probably do that through some sort of cross-sectional committee of some sort of teachers, principals, or whatever. And then that group would seek out different vendors. OK, which one is the appropriate solution? And they would prescribe some sort of rollout process.*

This process, however, is not always a quick one. For her district, Erin shares that it is a long, ongoing process any time they make any type of change, especially because the amount of time it is going to take in professional development just to get everyone to a new system in itself is challenging. Once a new technology is adopted, the implementation phase, more often than not, relies on the train-the-trainer model. For example, Bradley states that they start by training principals, who then train their campus staff.

For Ashley, building a professional learning community culture when looking at student data are an important support mechanism. In that space, she mentioned teachers can discuss common formative assessments, which they can use to adjust instruction or do flexible grouping. Doing so can help develop learning targets and help with assessing students and examining that data on a more routine basis, rather than waiting for a quarterly assessment to have a big meeting. At that point, she feels that it is so distant from when that content was taught. Her rationale is that it is harder to go and backfill gaps or reteach things. The professional learning community model is used by many other districts in the region, which might help with the culture-building process.

Ashley shares two other important elements for a successful implementation, based on her experience. First, many districts without sufficient capacity bring an implementation specialist in to train everybody. However, she argues that if it does not get embedded in the campus or the culture, it falls apart when that person goes away. Second, she suggests that teachers need carved out time to use the tools. Without it, “you can spend all the money, the teachers can have all the training in the world, they can know how to use it, if they don't have time built in to be able to do that, then that goes away.” As mentioned earlier, time is an essential component for stakeholder buy-in and the success of an implementation.

A key issue that multiple people elucidated was about long-term vision and commitment to the adoption process. In particular, Ashley mentioned that:

> *A lot of times districts just think about training, but they don't really think about that in terms of ongoing support and sustainability. So, for example, we had a data management system in the district that I was in, and everybody got training on it in the very first year. But then there wasn't a lot of sustainability planning or check points, like a five-year plan. Where do we want our teachers to be in two years? Should we be collecting some kind of data to see if they do know how to use it? Or if you're using these reports, like we thought they would?... So you spin your wheels a lot in districts if you don't think long term, five to seven years, what does it look like? Where do we want to be at the end of seven years with this?*

Ashley has strong concerns for districts that do not do long-range implementation planning for any kind of initiative, especially one that has significant financial cost, only to find out that nobody is using it. Michael, echoes this sentiment, stating that he hopes that districts are not just changing every year. He instead feels that longevity holds the key to results. Additionally, Michael warns against wearing out teachers by changing something every year and to vet carefully. He asked, “is it going to improve along the way in five or 10 years? Or is it something that's only there for five or six years, and it's probably going to go away?” By committing to the process, districts have the ability to better evaluate what is working, what is not working, and potential ways to remedy it without jettisoning a large, expensive technology investment.

In summary, school districts are relatively well-positioned in terms of adoption processes, and hardware and software infrastructure. However, they often do not have sufficient staff or knowledge and skills to fully implement large-scale learning data and analytics initiatives. Districts might also lack strategic vision and commitment toward iteration and improvement that could lead to the successful use of learning analytics. Next, I describe findings about data and technology literacy.

Greater technology literacy than data literacy. K-12 leaders in this study have significant experience with educational technology, including learning management systems, adaptive courseware, tutoring programs, and numerous phone apps. The use of technology in the classroom has become prevalent with many districts even have a one-to-one setup where each student receives a laptop. This level of access, while often siloed in different systems, provides significant opportunities to collect learning data; however, there is a significant gap in educators understanding their classroom data and how to make it actionable.

Part of the challenge is the culture of each school district and the level of the leader. For example, as a superintendent, Michael has a monthly meeting with the curriculum director and the principals where they sit down to talk about their most recent data. He feels that the data pieces are so much easier to understand than they used to be and can be broken down into core areas. He feels that this is “much more appealing to see.” Early on, his district primarily had raw data, which was ineffective, but they now have the ability to repackage and clean data before sharing with their teachers. He feels that doing so is better and more helpful for them. As a campus administrator, Britanny feels that the data she receives is still very confusing and wishes that there was a way to put data in layman's terms to make it much more understandable. She recognized that her district also breaks down data to make it more digestible for campus staff. Laurie continues by stating that “the more clarity we have as leaders, then the more clarity teachers have.” It is clear from the sampled locations that in many districts in the region, most data is managed centrally. This primarily stems from employing staff who have the ability to understand more granular and messier types of data.

This is not to say that schools are not trying to build capacity. In fact, their tactics cover a wide range. Paul’s district provides student holidays so campuses can have a “data dig day,” which primarily focuses on item analyses for tests by subject teams. Natalie remembered her district empowering students to track their data, but mentioned that “the teachers received, like, one day – or not even a whole day – just, this is how you do it, and now you're going to do it.” James said that his district goes over reading data annually, but that it has “become so blasé to the faculty that they become just immune to it.” These limited efforts are not sustained enough to build capacity around understanding learning data in a meaningful way.

To get around it, some simply hire consultants to help on their campus. Pearl states that it is not that administrators are not smart enough, but that their expertise lies in other areas. Therefore, it is better to let somebody else do data work for them. Michaela is a good example of this practice. She shared that she has funding to pay a consultant to help her look at reading and writing data. The consultant helps her make decisions about proper interventions and also helps train her teachers about their specific data. Ultimately, Michaela leans heavily on the district's testing and accountability department because they do a lot of the data analysis for her. She receives reports and feels that they do a good job with it

However, not all districts collect and make use of their data. Ashley shared that:

> *There are other districts who know they're supposed to be looking at data, but they don't really have maybe a lot of training kind of behind what kinds of information you can get from certain data points and really what you can't tell from certain data points without additional indicators or other evidence… I've gone to some districts where they never look at data still. Maybe the principal sits in their office and they pull up some tests and things like that, but it's not a routine part of the practice, where teachers are sitting down and looking at data together. It's all very kind of closed off. And nobody shares how their kids did on a test or how they're progressing or whatever.*

She continues that even when they do use it:

> *Very few people actually translate [data] into some sort of actionable intervention or solution that really pushes their kids where they want them to go. And the ones in my experience that I've seen do the most with that, it's really about the kind of that collective efficacy of the teachers or the administrators or whoever is in there trying to solve those problems collaboratively together.*

Robin shares a similar train of thought, stating that "our literacy level is not very good or it's not where we want it to be" He feels that one of the main reasons for it is being overwhelmed by the amount of information to where leaders do not have a focal area. By losing focus, districts "try to address too many things, or you don't really end up addressing what the real cause is." In an era of data-driven decision making, not being able to identify issues, and then implement, measure, and evaluate interventions, poses significant challenges for educational leaders.

One way that K-12 leaders feel that capacity can increase around learning data and the potential use of analytics is through a change in educator preparation programs. Instead of placing a substantial burden on school districts, changing what pre-service teachers learn prior to entering the classroom could have a major impact around data culture. Erin suggests that:

> *It's almost impossible for them to prepare them for something specific. But I think them understanding concepts of, hey, here's different samples of data. What do you see? What would you do? How would you adjust your instruction? What do you think? Getting just teachers to understand when something is not as high as you want to be, well, that's as a teacher issue. It's not a student issue when this person's kids are low.*

Britanny shares this sentiment, stating that:

> *What we're asking our teachers to do today with this inordinate amount of data that we have, but they've never been taught how to do that. So bring that down to the college level and make it a class of data analysis, and write your lesson plans. Here's your set of data. We're asking assistant principals to do it in interviews. We're asking principals to do in interviews. So we have to look at school data and prepare a plan, but teachers aren't coming to us being prepared on how to do that-- look at data and develop a plan for children.*

Jim feels that the onboarding process might take a brand new teacher several years to really understand what they need to do. If they came into the classroom with better understanding of data and how to think critically about it, teachers could be empowered to improve outcomes for all learners earlier in their careers instead of being told what to do and what to look for.

Currently, he suggests that they're not investigating and drilling on their own. This could have a positive impact on building a culture for learning data and analytics, leading to widespread institutional change.

While educators make use of different technologies in their school districts, far fewer have the expertise regarding data. The data that they typically use is high-level or tied to state objectives/standards, but much less formative and integrated datasets are used in day-to-day practice. One-off trainings do not appear to have much success for building capacity, and campuses often have to rely on consultants or central offices for help. However, one potential solution might include changes to pre-service teaching curriculum to match the data-driven culture that new educators will work in. In the final section, I share findings about school district size and location.

Discrepancies between district size and location. The research sites for this study includes a range of contexts, from small to large, and rural, suburban, and urban. A number of the participants recognized the differences between the school settings, primarily sharing about the challenges on working in a smaller district. Pearl stressed the challenges of scaling large technology implementations in little districts, stating “because we see that even with Canvas, and we work with them, and even trying to adopt in LMS is challenging when you're the single technology person.” Natalie calls these individuals “singletons” who “wear multiple hats” in the district, meaning that they often have multiple responsibilities. Michael, a superintendent, shares that:

> *In a smaller district, we don't have that kind of staffing, and our larger districts do. So a lot of times we lean on like [neighboring districts], or even larger districts down south-- or north from us that they can give us some of that feedback on, this is what we've*

learned. And so go into those curriculum director meetings and those kind of things is where we can get a lot of that.

Besides staffing, access to technology and funding pose serious challenges for small, rural districts. Michael continues about his district:

> *Our internet capabilities, we've done quite a bit here in the last three years, in that we have a continuous loop of fiber, and we're actually still on the internet system where it's through a tower… we're supposed to be connected to a wireless internet, and we're going to have 500 something megs, or whatever it's called, and we're going to be in the gigabytes by then.*

While it might seem asinine that a school district near the Dallas-Fort Worth metroplex would not have high speed technology in the late 2010s, some districts face slow speeds, which can limit the capacity for use of large-scale learning data and analytics.

Some rural districts on the fringes of the metroplex will face explosive development, which could create significant growing pains. Paul mentions that his school does not have the community partners to do what they need to do, but that they are going to get there. Additionally, growth is coming with the anticipation of doubling in size in the next four years. The community is still largely agricultural, where kids work for their parents in addition to schooling. This can lead to excessive absences and can lower student outcomes. As they grow, Paul mentions that "kids should have every opportunity" and that the "big district that you look up to - we're trying to get there."

Given that rural schools make up a significant portion of Texas, further investigation into these districts are warranted. Jim stresses that:

> *I think we don't want some of our kids to get the data analytics, we want all the kids to*

get that. And so I think about most of the school districts in Texas, they're probably under 10,000, maybe even under 5,000. I don't know the stats on that. I think that could present a huge challenge to those districts. And even at that, they might be depending on third-party systems. But it's like, this third-party system does this silo, this third-party does this. But no one's crunching it for the whole kid. And I think that's where I think we can all do a better job. But bigger school districts are probably doing better, just because they've got to help 30,000 kids versus 120.

Economies of scale can be a significant factor in procuring services, but Jim highlights the potential growth of inequity between have and have-not districts.

This does not mean that large, well-funded districts are without their challenges. For example, Robin states that in some larger districts, technology adoption “gets very political because there's a lot of dollars involved.” Laurie also shared that large districts often limit the tools that educators can use, which can stifle new ideas. Finally, James said that “being a district the size we are – one high school, one junior high – once you've got the standard operating procedure, it doesn't change much,” meaning that it can be easier to understand processes over large districts.

The participants from this study came a variety of backgrounds and presented discrepancies between rural and suburban/urban school districts. Funding, technology access, and staffing play a role, which can potentially increase inequities across Texas schools. Further research can help illuminate these factors in order to help promote greater student success for all learners.

Summary

At the beginning of this chapter, I share details about the diverse set of study participants.

I then present the findings from my qualitative research into factors that can promote and hinder the adoption of learning analytics. These factors include (a) knowledge, (b) perceptions and attitudes, and (c) capacity. In the final chapter, I discuss the implications of my findings as well as considerations for policy, practice, and future research.

Chapter Five

Discussion

In this chapter, I present a brief overview of the study. Next, I summarize the key findings and discuss how they relate to prior research. After discussing the findings, I provide implications for future policy, practice, and research. Finally, I share why this research study is significant before concluding.

Summary of the Study

Learning analytics has emerged as a data-driven way to improve learner outcomes over the past decade (Agasisti & Bowers, 2017). However, as the adoption and implementation of learning analytics continues to surge, there are some significant barriers to this process, such as stakeholders buy-in (K. Sun, Mhaidli, Watel, Brooks, & Schaub, 2019), training and support (Tsai & Gasevic, 2017), concerns over privacy and ethical issues (Slade & Prinsloo, 2013), the quality and appropriateness of tools provided by third-party vendors (Siemens, 2012), and institutional capacity to collect and meaningfully analyze and interpret data (Pak & Desimone, 2019). Poor implementation can increase inequities (Tawfik et al., 2016), squander public funding (Ross, 2015), foster stakeholder resistance against future initiatives (Mohammed & Harlech-Jones, 2008), and ultimately lead to abandonment. Another challenge stems from the need for educators to not just understand a new tool, but the data that goes into and comes out of it (Ahn, Campos, Hays, & Digiacomo, 2019). While there has been a growth in research on the learning analytics adoption process in a higher education context, little has taken place in K-12.

The purpose of this dissertation is to investigate key factors that may promote or hinder the decision to adopt learning analytics in North Texas K-12 schools by leaders. To do so, I adapt the Multicultural Competency framework (The Tilford Group, 2001) of knowledge, attributes, and skills to explore psychosocial factors of leaders at the campus, district, and educational service center levels as well as how school district and individual capacities influence the decision to adopt learning analytics. I make use of the following research questions to guide my study:

1. How do psychosocial factors (perceptions, attitudes, and understanding) of K-12 campus and district leaders in North Texas promote or hinder the decision to adopt learning analytics tools and large-scale learning data?
2. How does internal (skills) and district (guidelines, training, support, technology and data infrastructure) capacity promote or hinder K-12 leaders' decision to adopt learning analytics in North Texas school districts?

Given the exploratory nature of the study, I used a qualitative approach (Charmaz, 2014; Creswell & Poth, 2017). My primary data source was semi-structured interviews with leaders in rural, suburban, and urban districts, along with the Regions 10 and 11 service centers. I chose to investigate leaders over other stakeholders given their role in the adoption process, whereas other groups, such as teachers and students, play a bigger part in later implementation phase. I reached saturation at 14 participants that had seven females and seven males, all with master's degrees or doctorates and between 10 and 39 years' experience as an educator. Four leaders worked in educational service centers, five worked as campus administrators, and five worked in a variety of roles in district offices. All had neutral to extremely positive attitudes toward new technology, innovation, and risk taking. Unfortunately, challenges during recruitment led to a sample that was not diverse. Overall, 11 participants identified as White, one as White/American Indian, and two as Hispanic. While the majority of educational leaders in the region may be White, lack of sufficient diversity does impact the findings of this study and more research is needed to better determine its representativeness and potential issues around power balance.

I recruited participants by email addresses collected through school district websites, personal networks, and snowball sampling. Interviews took between 21 and 69 minutes, averaging around 50 minutes to complete. Five interviews took place in person and nine took place online via the Zoom web-conferencing software. I transcribed all audio files and used line-by-line coding (Charmaz, 2014) to develop a preliminary set of codes, and then axial coding (Saldaña, 2016) to find relationships and collapse codes into categories. After the data analysis, I shared the transcripts and preliminary findings with the participants for feedback and to help ensure the trustworthiness of my interpretation (Creswell & Poth, 2017). Throughout the process, I wrote memos to iteratively develop my ideas before collapsing categories into emergent themes (Charmaz, 2014). In these memos, I considered factors such as the number of campus and district staff, the condition of buildings and infrastructure, and participant body language when responding to interview questions. I also explored district website content pertaining to key issues, such as policies and/or guidelines around the use of student data, and included those findings in the memos. In the next section, I summarize these themes as key findings from this study and discuss them in greater depth in the context of the two research questions.

Summary and Discussion of Key Findings

During my analysis, three major themes emerged from the data. I aligned them with the adapted Multicultural Competency framework, which originally includes (a) knowledge, (b) personal attributes, and (c) skills. In this dissertation, I employ this framework to investigate relevant psychosocial factors, including perceptions, attitudes, and understanding (research question #1), and capacity (research question #2) around potential learning analytics adoption (Figure 5.1).

Multicultural Competency Framework	Research Question
Knowledge………………………..	#1 - Psychosocial Factors
Attributes………………………….	#1 - Psychosocial Factors
Skills………………………………	#2 - Internal/External Capacity

Figure 5.1. Alignment of Multicultural Competency Framework and research questions.

Knowledge in the context of this study is understanding about large-scale learning data and analytics. Attributes does not match as directly and I adapt it to include perception, attitude, and participant background, such as their experience or positions. I suggest that these psychosocial and background factors can influence the decision to adopt learning analytics, much like traits can. Finally, I adapt skills to include both internal and external capacity for learning analytics, such as district support, training, guidelines, and adoption mechanisms, and individual use of data and technology. I discuss these themes and their subthemes in the following sections.

Knowledge

This theme aligns with my first research questions about psychosocial factors that might promote or inhibit the adoption of learning analytics. Knowledge, in this context, relates to understanding about large-scale learning data and analytics. Two major subthemes emerged that help to support it: (a) leaders' understanding of learning analytics and large-scale learning data varies significantly and (b) leaders inform themselves about trends and innovations in different ways.

Understanding of learning analytics and data varies. Overall, most participants emphasized that they primarily use data at the state standard level, while a few shared about more granular and integrated datasets. The Texas Essential Knowledge and Skills, or TEKS, are the state standards that students must meet between kindergarten and twelfth grade. Accountability and funding rely on them, and standardized tests have grown as a key way to assess mastery at the expense of other means (Scogin, Kruger, Jekkals, & Steinfeldt, 2017). Although this finding is not unexpected, it presents incongruities with the data needed for learning analytics (Nistor & Hernández-Garcíac, 2018).

In particular, leaders continually mentioned the data that they currently employ, typically state data, curriculum assessments, and benchmarks, which are snapshots of certain times of the school year and are not useful at the day-to-day level. However, Laurie, a campus principal, recognized the potential data needs to use learning analytics, saying, “you have to have so many data points, because each piece of data is going to paint a different picture for a learner.” Bradley, an assistant superintendent, sees it a little differently, stressing that “data is just data. Now, how do we use it to actually improve something, whether that is the actual student achievement in the classroom for individual students or the system on how we assist teachers in improving student achievement?” Ashley, staff in an educational service center, goes further, stating that data is really part of the inquiry process and “it's supposed to make you ask some questions. And oftentimes I see a lot of people that immediately jump to conclusions based on what they see, rather than using that as a launch point for inquiry.” While leaders may not currently have a full understanding of what data is needed, they are able to recognize that what they are currently using is not sufficient.

Out of this research sample, job titles also play a role in understanding learning analytics. Campus leaders discussed the potential to improve instruction while district-level leaders focused more on supporting the use of data in classrooms to improve student outcomes, specifically by increasing the speed by which teachers and campus leaders could access it.

Leaders in service centers had a more critical and global view, concentrating mostly on increasing the amount of data collected while also taking a tougher look at what data educators use for analyses.

In general, campus administrators had the least knowledge about learning analytics prior to the interview. While there is no literature to build on, this result is not incredibly surprising given the scope of the position. I suggest that because campus leaders have a smaller piece of the overall puzzle and more limited ability to purchase technology, central office leaders that have to serve the needs of an entire district and service center staff that have to serve well over 100 districts have more of a big-picture view of the educational landscape. Since the procurement of a learning analytics solution would also more likely to take place at the district level, it is far more likely that vendors would target others who might have influence.

Inform themselves in different ways. To learn about new innovations and trends, the participants made use of a wide range of options. Some sought simplified online sources that summarized information while others dove deeper into white papers. Attending conferences and meetings provided face-to-face opportunities to discuss emerging areas and lessons learned.

Most critically, only one participant mentioned academic journals as a way to better inform themselves. Given that learning analytics is a relatively young field of research and practice (Siemens, 2012), tools and methods are still just beginning to gain traction in K-12 and postsecondary contexts (Freeman et al., 2017). As schools continue to adopt and implement learning analytics solutions, there is a likelihood that the evidence-based frameworks (Macfadyen, 2017) emerging in academic sources might not be readily available to support leaders through the transformation.

Perceptions and Attitudes

This second theme also aligns with my first research questions about psychosocial factors that might promote or inhibit the adoption of learning analytics. Perceptions and attitudes, in this context, relates to how people perceive and feel about large-scale learning data and analytics. Two major subthemes emerged that help to support it: (a) leaders are conflicted about the available data that they have and (b) leaders perceive numerous challenges, opportunities, and concerns about the use of learning analytics in a K-12 context.

Conflicted about available data. School districts in the region currently collect significant amounts of data and build it into their culture. Some leaders believed it was essential to their jobs and enjoyed looking at data; however, they often feel overwhelmed by the current volume of it. Overall, the majority of leaders spoke more negatively about how data was currently being used than positively. They expressed concerns about not having enough time to use it effectively, not having it in real-time, having to look for it in a number of disconnected systems, and it being used in punitive ways against students and educators. This presents a significant challenge for districts that want to adopt learning analytics.

It is likely that educators will be required to increase the amount and types of data that they use. Without proper long-term support and training, a means to provide additional time without adding workload burdens, and being used to improve outcomes and not punish for shortcomings, educators will likely have great anxiety about the adoption and be resistant to the process (Aldunate & Nussbaum, 2013; Chiu, 2017; Hancock, 2012; Shattuck, 2010). Ultimately, leadership positions must drive the change process and must be intentional with it while working with a myriad of stakeholders (Cho & Wayman, 2014; Graves & Bowers, 2018; J. Sun et al., 2016).

Numerous challenges, opportunities, and concerns perceived. During the interviews, I asked leaders about their perceptions regarding challenges and opportunities, as well as any concerns that they might have about using learning analytics and large-scale learning data. I share the results of these three subthemes in the following sections.

Challenges. Three main areas emerged pertaining to challenges. First, leaders shared issues around using data. These issues include poor communication between stakeholders (Reinintz, 2019; Tsai & Gasevic, 2017), making data actionable (B. C. Phillips & Horowitz, 2017; The Learning Counsel, 2019), and turning around data quickly enough to be effective (Beer, 2019). Most of these challenges were shared by district and service center leaders. Next, school district relationships with third-party educational technology vendors led to issues around the quality of the products (Dobo, 2016), as companies routinely overpromise what their products can do (Boobier, 2018), and prohibitive costs to adopt and implement products (Digital Promise, 2014). Lastly, the structures within school districts can create barriers, with unique issues pertaining to size (Stewart, 2018; Tyler-Wood, Cockerham, & Johnson, 2018), variability between campuses within a district (Brunner, Keller, Wenger, Fischbach, & Lüdtke, 2018), and systemic pressures that come from trying to improve state ratings (Heilig & Darling-Hammond, 2008; Loeb & Byun, 2019).

Opportunities. Participants also highlighted a number of opportunities that learning analytics could bring and three main areas emerged. First, leaders envisioned the prospect of supporting the individual student context. This could be through personalization of content (D. Liu, Bartimote-Aufflick, Pardo, & Bridgeman, 2017), empowerment using their own data (Mathewson, 2017; Wittebols, 2016), and painting a more holistic view of each learner (Ahad, Tripathi, & Agarwal, 2018; Wong, 2017). Next, the interviewees felt that adopting and implementing learning analytics could subsequently lead to quicker access to data (Beer, 2019).

Additionally, districts would collect greater amounts of learning data about their students that could be linked together (Zouaq, Jovanovic, Joksimovic, & Gasevic, 2017). Finally, leaders felt that there was greater explanatory power (Joksimovic, Kovanovic, & Dawson, 2019) than what educators currently have in their toolkits. A key reason is moving away from summative snapshots and toward more formative assessments, which paint a more complete picture of the learning process over time by better identifying gaps along the way.

Concerns. The last item in this section is concerns, which illuminated four key areas for discussion. First, leaders had significant concerns about the security of digital learning data and potential privacy issues that could arise from breaches (Kurshan, 2017; Nazerian, 2018). Second, interviewees shared questions about stakeholder awareness (Slade & Prinsloo, 2013; K. Sun et al., 2019) and data ownership (Rodríguez-Triana, Martínez-Monés, & Villagrá-Sobrino, 2016; Steiner, Kickmeier-Rust, & Albert, 2015). For example, should parents own student data and be able to make decisions about its storage and use? Next, leaders discussed apprehension about districts properly using data and the appropriateness of algorithms (B. H. Khan, Corbeil, & Corbeil, 2018; Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016; O'Neil, 2016). An example could be predictive systems pigeonholing students into specific educational tracks without them having agency in the process. Finally, participants questioned whether educational technology investments were worth it, given meager gains in key areas with prior implementations (Boninger, Molnar, & Saldaña, 2019; Sadwick, 2019).

Capacity

The final theme aligns with my second research questions about factors that might promote or inhibit the adoption of learning analytics. Capacity, in this context, relates to internal skills and external support and structures for large-scale learning data and analytics. Three major subthemes emerged that help to support it: (a) districts mechanisms and infrastructure for adoption, (b) greater technology literacy than data literacy, and (c) discrepancies between district size and location.

Districts mechanisms and infrastructure for adoption. North Texas school districts in this study have a robust technology infrastructure and mechanisms for adopting new tools. These include policies and guidelines, professional development and training, and use of professional learning communities and train-the-trainer models for diffusion. However, not all districts had sufficient staffing or knowledge to implement a large-scale learning data and analytics initiative. Additionally, leaders expressed concerns over long-term commitment and strategic vision (Topper & Lancaster, 2013). Without sustained efforts, technologies are frequently dumped in favor of new ones, most notably when senior leadership changed. Finally, districts did not have any substantial public-facing policies or guidelines on their websites around the use of learning data, nor did they have procedures in place around technology adoption. Some of the leaders mentioned that these were typically internal, handled through emails or handbooks that were not disseminated beyond campus and district staff.

Greater technology literacy than data literacy. The findings indicate that the participants have far greater experience and expertise with technology than they do with data. Educators use technology throughout the day, such as digital attendance systems and gradebooks, behavior systems such as ClassDojo, tablets for reading, adaptive courseware for reading and math development, and parent communication systems. However, educators receive far less training for the data that they use, which often occurs in small snippets of time. Because administrators and teachers do not have strong data skills, they are often reliant on consultants or the central office to clean, organize, and guide them through what they have. Leaders suggested that revising the pre-service teaching curriculum could be a critical step in building overall capacity.

Discrepancies between district sizes and locations. There are significant differences between small, rural districts and large, suburban and urban districts with regard to their capacity to adopt learning analytics. For example, one of the rural districts had 10 total people in their central office, whereas one of the large, urban districts had 15 in their research and accountability department alone. Furthermore, one superintendent noted that funding impacted his rural district's ability to be innovative and use new tools and technologies, and that they often had to lean on neighboring districts to determine what they should adopt.

In these sections, I highlighted the emergent themes from the study through the lens of research questions asking about how psychosocial factors and capacity could inhibit or promote the decision to adopt learning analytics. While a significant amount of data that I collected remained, these themes and examples best exemplify the answers to those questions. In the following sections, I discuss the findings' implications for policy, practice, and research.

Implications for Policy

As Michael (superintendent) identified, his rural district was just beginning to have high-speed internet that was comparable to other districts. This problem is not limited to his district (Foresman, 2019) and highlights important policy issues in Texas and nationally. As state and federal agencies consider funding strategies, needs like this one should be addressed. In Texas alone, a 2016-2017 report mentions that about half of districts are considered rural and serve fewer than 1,000 students. (Ghazal, Harris, McCann, & Neeley, 2018). The Texas Education Agency website, citing data by the U.S. Department of Education's National Center for Education Statistics, states that the number is actually greater than 2,000 campuses and that

Texas has more schools in rural areas than any other state (Texas Education Agency, 2019). Access to current technology is paramount for supporting initiatives to close gaps through data-driven efforts. Failing to achieve it will likely increase inequities across the state.

Second, given the increasing demand for data-driven decision making and evidence-informed practices in the K-12 public school space, foundations, as well as federal and state agencies, should consider funding ways to remove barriers for adoption and increase successful implementations across the learning analytics ecosystem. This ecosystem includes all stakeholders, ranging from students and their families to practitioners, administrators, technology staff, policymakers, educational technology and courseware vendors, intermediary organizations like the IMS Global Learning Consortium, and funders. Barriers also include the burden of technology costs to use learning analytics tools and methods, especially in high-need districts.

Finally, with the rise of data and technology in K-12 districts, educator preparation needs to include more emphasis on understanding and thinking critically about learning data as a core, 21^{st}-century teaching skill. The leaders that I interviewed shared that their staff do not have sufficient data skills at present. Incorporating even more data will only compound the problem and district trainings are often inadequate for long-term capacity building as they are not sustained. However, attacking the problem at the preparatory stage would likely help alleviate anxieties for early-career teachers, who are often overwhelmed their first few years as they improve their practice. By diminishing the data barrier, teachers can potentially have a corresponding increase in student learning outcomes and help school districts focus on other areas for professional development.

Implications for Practice

First, as I found in the initial theme of knowledge, K-12 leaders at all levels need to begin to better familiarize themselves with additional types of data and emerging learning analytics techniques. Doing so now can help them to get ahead of the adoption curve. Additionally, greater awareness can build trust and stakeholder buy-in throughout the district and create a more unified vision for learning analytics adoption and implementation. For example, a major challenge that I faced in this study was during recruitment. I reached out to numerous leaders in different positions who either felt that they were not qualified to answer my interview questions or simply insisted that I reach out to data and accountability groups. This persisted even when I explained why I thought that their position would be critical for understanding factors that could promote and inhibit the decision to adopt. The majority of these positions included instructional technologists, professional development coordinators, information technology leaders, curriculum directors, and testing coordinators. As Ashley remarked, strategic vision for projects like these can go a long way in helping to ensure its success. The perception that data people only focus on data and technology people only focus on technology does not see the wider implication for how many different people in a district might use learning data for varied purposes. The use of learning analytics might also hold the potential to shift current roles to be more comprehensive, where the positions are more aware of how data can impact decisions around items such as curriculum, design, technology procurement, and accountability and reporting. Some researchers have also called for new educational data scientist positions taking lead roles in schools to help drive data-driven decision making (Agasisti & Bowers, 2017).

Second, leaders who purchase technology for their districts need to think critically about issues found in the second theme. Participants identified numerous challenges and concerns around the use of large-scale learning data and analytics, including data privacy and security, appropriate collection and use of data, and high-quality algorithms that fit the context of that school district or campus. Schools need to ensure that students and teachers are protected from external threats, but also internal punishment from improper and unethical use of granular learning data and analytics. Doing so can build stakeholder buy-in and trust, and will likely improve student outcomes. Otherwise, they might be used to automate inequality, particularly for at-risk populations (Eubanks, 2018).

Third, leaders who purchase technology need to have a long-term strategic vision in order to ensure that there is enough time to properly evaluate and make adjustments and improvements. For a new leader in a district, this might mean not immediately overhauling a system or bringing what they had previously used with them. Failure to do so could increase initiative fatigue among students, teachers, and campus leaders, waste taxpayer funding, and potentially halt progress currently being made.

Fourth, school districts can use an inquiry model about their data, rather than those that might just take it at face value. At higher levels, this might mean inferential statistics instead of only looking at descriptive reports. As schools begin to use more granular and complex learning data, they can begin to ask different questions about their students, and bring them into the process to promote inclusion, ownership, and data literacy.

Finally, feedback mechanisms between vendors and districts could help to improve the quality of the products offered. For example, regional service centers could assist with championing an event, or conduct a survey, in order to determine needs and the best possible solutions. Going through a service center might also provide additional bargaining power, as vendors could make changes that cover a larger set of districts instead of one-by-one. This might be a way to help reduce costs, which leaders identified as a significant area of concern.

Implications for Research

At the conclusion of this research investigation, there are a number of important implications for scholars to further investigate. First, given the limited nature of the size of the qualitative study, additional research needs to take place in order to better develop a broader understanding of what may promote and hinder the learning analytics adoption process in K-12 schools. This research could further investigate differences between leader characteristics, such as educational background, perceived innovativeness, gender, and race, and district characteristics, such as size, funding, and demographics.

Second, future qualitative and quantitative studies will lead to the development of an evidence-based framework that can guide leaders through the process (e.g., Tsai, Moreno-Marcos, Tammets, Kollom, & Gašević, 2018). Since I found that few leaders read academic journals, researchers who want to support transformation in school districts will need to find ways to translate their findings and share through less-formal mediums. This might include magazines, news media, and blogs that have relatively high readership. For example, some leaders read resources from the International Society for Technology in Education (ISTE), Texas Computer Education Association (TCEA), or EdSurge.

Third, as some school districts have begun to adopt and implement large-scale learning analytics projects, researchers can explore potential differences between those with no exposure. This would lend itself to additional measures, such as self-efficacy (Bandura, 2006; Ozerbas & Erdogan, 2016) with learning data and analytics. Additionally, curating a set of lessons learned could inform adoption efforts by future K-12 districts.

Fourth, subsequent studies could further investigate the relationship between leaders/districts and third-party vendors who offer learning analytics solutions, which are often quite expensive and do not always fit in a certain district's context. Education systems spend over 10 billion dollars on technology (Sadwick, 2019), but as the findings showed, most leaders feel dissatisfied with products and interactions. Additional research into the alignment between capacity and needs is a good starting place. Given the concerns over the quality of the tools and algorithms, further investigations should take place.

Next, I faced difficulties getting access to some districts due to their review board policies. Researchers who want to work in this K-12 space will need to incorporate long windows in order to complete this type of study. Some of the districts that I contacted had policies of no fewer than 90 days to get a positive or negative response. Additionally, some district review boards asked me to modify my research protocol, typically to reduce the participants' time commitment, which led me to choosing other districts in order to use the one that was approved by my dissertation committee and our university's institutional review board. This potentially impacted the diversity of participants due to access.

Finally, more research needs to take place with other stakeholders. This could include students, parents, teachers, school boards, and state policymakers. While their voices might be less relevant for adoption than implementation phases, talking with these groups will help to paint a more complete picture of the complexities of the larger process, possibly amplifying concerns around some barriers.

Significance of the Study

This findings of this study are significant in four key ways. First, few scholars have investigated the adoption of learning analytics in a K-12 context. In a higher education context, major funded projects have occurred in the European Union (Tsai et al., 2018), Australia ("Learning analytics in Australia home page," 2017), and Latin America (Ochoa, 2019), and more work is beginning to take place in the United States (Sclater, 2019). While not centered on adoption, significant research and efforts have also occurred using learning analytics for informal learning settings, such as massive open online courses (e.g., Liu et al., 2019), and for reskilling the workforce (e.g., Phillips, 2019; Reinitz, 2019). By sharing the perspectives of K-12 leaders, I provided contributions to a new area of research in a rapidly growing space (Freeman et al., 2017).

Second, researchers have studied both the adoption of educational technologies in K-12 schools, such as electronic textbooks (Chiu, 2017) or computer games (Kebritchi, 2010), and the need for teachers to gain better data literacy (Mandinach & Jimerson, 2016). The use of learning analytics presents a unique challenge of requiring educators to know both. Understanding of one, but not the other, will likely diminish the effectiveness, and there is a critical adoption literature gap considering them in tandem in the K-12 context. In this study, I addressed both elements and how they might have an impact on adoption as the use of learning analytics will push data from state standards and objectives to more complex phenomenon and more frequent use.

Third, I identified potential areas of disconnect between different types of leaders. Instead of solely focusing on a single job title, I explored a variety of positions at campuses, districts, and service centers. I also interviewed different campus leaders from elementary, junior high, and high school levels. Doing so illuminated how certain leaders might have different perspectives than others, which has the potential to create barriers when adopting learning analytics broadly. This opens the door for future investigation into perceived needs of these leaders who want to use large-scale learning data and analytics.

Finally, I uncovered differences between small, rural school districts and larger, suburban and urban ones. Leaders shared perceived and actual challenges pertaining to size, location, and funding, and how the challenges impacted their ability to make use of innovative technologies and approaches to improve student outcomes. Since the use of learning analytics in certain districts might not be achievable in others, there is the potential to further inequities across the State of Texas. Given the large number of rural school districts, this is a critical conversation that should take place going forward among policymakers and funders.

Conclusion

There is currently a gap in the literature about factors that might promote or hinder the decision to adopt learning analytics in the K-12 public school context. While the learning analytics research community has largely focused on postsecondary and informal learning contexts, this dissertation provides an early effort at better understanding challenges and opportunities, and how learning analytics might play a role in schools moving forward. This qualitative study includes participants from North Texas, but future work can build on it by investigating different regions and including other stakeholders, such as students, teachers, and policymakers, who play a role in the adoption and implementation of new technologies.

There are many obstacles ahead for school districts that want to use large-scale learning data and analytics. In order to maximize the effectiveness, school districts need to build further capacity and knowledge, focus less on summative snapshots and more on integrated, granular learning data, and have more long-term, intentional commitment to iterating and improving on new approaches rather than quickly moving onto something new without giving time for proper evaluation. Funders and policymakers need to foster an environment that promotes cultural change that moves data from being a burden and difficult to access to something that educators can better use to improve student outcomes. This includes enhancing data ecosystems, decreasing the technology divide between rural and (sub)urban districts, providing sustained training and time for teachers to analyze and dive deeper into their data, and updating preparation programs for both teachers and administrators to incorporate these practices. Vendors must be more responsive to school district needs and offer high-quality products that conform to security and ethical standards, including algorithms, privacy, and stewardship. Despite these obstacles, the promise of using learning analytics to improve outcomes is significant and rapidly growing, and this dissertation provides a starting place to understand how schools might effectively use it.

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Appendix A

Interview Protocol

Semi-structured Interview Questions (and potential prompts):

1. What types of student learning data does your campus/district collect? How is it stored and shared? Why is your campus/district collecting this type of data? How do you feel about the collection of this data?
2. What strategies and policies does your district have for this learning data? Are these strategies/policies posted publicly? Have stakeholders (such as teachers, students, administrators) been trained to use it?
3. How would you define learning analytics? How do you feel about the use of learning analytics in the K-12?
4. Why might your campus/district want to adopt learning analytics? How do you think that the adoption would be accomplished?
5. What capacity does your campus/district have to support learning analytics work (such as staffing, funding, training, technology infrastructure, and stakeholder buy-in)? If you needed to increase your campus/district's capacity to support it, how would you go about doing so?
6. What are some of the challenges and opportunities that come from using learning analytics in K-12? What are some specific examples that might pertain to your district?
7. What do you feel are some possible ethical (ex: privacy, stewardship, opt in/out, transparency) considerations when adopting learning analytics in K-12? What are some specific examples that might pertain to your district?
8. What has been your experience with third-party educational technology vendors? What types of solutions did these vendors offer? (personalized learning, learning management

systems, analytics) Has a vendor offered what you would consider a learning analytics product? If so, what was your reaction to it?

9. How do you/does your campus/district make decisions about what technologies you adopt? What is the vetting process like? Does your district have established policies or guidelines about the adoption and/or use of educational technology?
10. How would you go about further informing yourself about effectively using learning analytics in your school district?
11. Do you have any comments that you would like to add about your experience using learning analytics that we haven't already discussed?
12. May I contact you again if I have other questions?

Biographical Information

Justin T. Dellinger has been a passionate educator for most of his life. Whether working as a summer camp counselor, soccer coach, youth mentor, Sunday school leader, junior high school teacher and coach, graduate teaching assistant, professional learning community facilitator, or university instructor, he enjoys seeing people grow in different ways.

Justin finished his Bachelor of Arts in History and Spanish from the University of Texas at Austin in 2004. He taught in Richardson ISD from 2004-2008 before starting graduate school at the University of Texas at Arlington. He completed his Master of Arts in History in 2010 and immediately began the Transatlantic History doctoral program. Due to some life changes, Justin transferred into the K-16 Educational Leadership and Policy Studies doctoral program at the University of Texas at Arlington in 2016. He has worked full-time at the university since 2012, starting as an instructional programmer/designer in the Center for Distance Education before moving to the LINK Research Lab in 2014, where he currently serves as Associate Director.

After graduation, Justin plans to move into a second phase of this project to expand the scope through quantitative research across Texas. He is currently pursuing funding to support this work. In addition to learning analytics adoption, Justin's other research interests include learning pathways design and institutional change.