Disrupting the Digital Norm in the New Digital Divide:
Toward a Conceptual and Empirical Framework of Technology Leadership for Social Justice
Through Multilevel Latent Class Analysis

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ABSTRACT


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The purpose of this three-article dissertation is to explore the intersection of educational leadership, instructional technology, and culturally responsive education in pursuit of a new leadership framework called technology leadership for social justice. This dissertation employs three emerging methodologies, namely three-step latent class analysis (LCA), multilevel latent class analysis (MLCA), and meta-narrative review, to examine typologies of teachers and their perceptions of technology use and technology leadership with large-scale, quantitative data and to offer a conceptual framework of school and district technology leadership through a culturally responsive lens. The first study utilized latent class analysis (LCA) with the NCES Fast Response Survey System Teachers’ Use of Educational Technology in U.S. Public Schools, 2009 (FRSS 95) dataset (n=2,764) to identify four different types of technology-using teachers: Dexterous, Presenters, Assessors, and Evaders. I also found that teachers in low-income schools are more likely to be in the teacher subgroups that use technology in less impactful ways in the classroom. The second study used multilevel latent class analysis (MLCA) with the 2011-12 Texas School Technology and Readiness (STaR) Charts (n=6,935 schools in n=910 districts) to find three subgroups of teacher perceptions of technology leadership at the school level, High STaR Schools, Moderate STaR Schools, and Low STaR Schools, and four subgroups of teacher perceptions of technology leadership at the district level, Model STaR Districts, High STaR Districts, Moderate STaR Districts, and Low STaR Districts. I found that the Texas teachers in
the school and district level subgroups with the lowest perceptions of technology leadership had the lowest student achievement outcomes and were more likely to serve students from historically minoritized backgrounds. The third study employed a systematic, meta-narrative review of the research literature exploring the intersection of technology, leadership, and culturally responsive education, integrating the findings from sixty studies into a conceptual framework of *technology leadership for social justice*. Each of the three dissertation articles explores the implications for the development of a more evidence-based, sociocultural conception of school and district technology leadership in research, policy, and practice.
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When things go wrong, as they sometimes will,
When the road you’re trudging seems all uphill,
When the funds are low and the debts are high,
And you want to smile, but you have to sigh,
When care is pressing you down a bit –
Rest if you must, but don’t you quit.

-- Author Unknown

Nothing truly prepares you for the intellectual and emotional demands of a doctoral program. It is truly a sprint and a marathon at the same time. I affixed a small postcard with the excerpt seen above to my computer during the final stages of completing my dissertation in order to motivate me as I finished my own race to the dissertation finish line. While these small nuggets of wisdom certainly provided much needed inspiration and perseverance whenever I doubted if I could actually finish, I realized that I also have a village of supportive mentors, family, friends, and colleagues who were truly instrumental in helping me achieve this monumental accomplishment.

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K.E.G.
DEDICATION

I dedicate this dissertation to the legacy of educators in my family –

my late grandfather

Kenneth Edward Graves

and to my late grandmother

Nina Mae Swain

– whose spirits impassion my present and future work as an educator.
Chapter I – INTRODUCTION

The purpose of my three-article dissertation is to explore the intersections of school leadership, educational technology, and culturally responsive education in pursuit of a new conceptual and empirical leadership framework called *technology leadership for social justice*. This dissertation seeks to aid current research, policy, and practice by examining typologies of technology-using teachers and leaders with large-scale, generalizable data to gain a more robust, sociocultural understanding of digital age leadership for learning and then explicating a new conceptual framework of school and district technology leadership through a culturally responsive lens. My first dissertation article, “Toward a Typology of Technology-Using Teachers: A Three-Step Latent Class Analysis (LCA) of the NCES Teachers’ Use of Educational Technology in U.S. Public Schools, 2009 (FRSS 95)” is one of the first quantitative studies to employ latent class analysis (LCA) with nationally generalizable data on teacher technology use available from National Center for Education Statistics (NCES). I find four different statistically significant types of technology-using teachers in U.S public schools, while also finding that two of the teacher subgroups who use technology in less meaningful ways are more likely to teach in economically disadvantaged schools. My second dissertation article, “To What Extent is School and District Technology Leadership Just ‘Good Leadership’? A Multilevel Latent Class Analysis (MLCA) of the 2011-12 Texas School Technology and Readiness (STaR) Charts” is one of the first educational leadership study to employ multilevel latent class analysis (MLCA) with the 2011-12 *Texas School Technology and Readiness (STaR) Charts* to investigate the extent to which there are different subgroups of teacher perceptions of technology leadership at the school level and to what extent the school-level subgroups are distributed across different types of school districts. I find three statistically significant subgroups of teacher perceptions of
technology leadership at the school level and four statistically significant subgroups at the
district level. While my findings suggest that technology leadership is indeed good leadership as
the school and district subgroups with the highest perceptions of technology leadership are
associated with the highest student achievement outcomes, I also find that the school and district
subgroup with the lowest perceptions of technology leadership had the lowest student
achievement outcomes and were more likely to serve higher percentages of historically
minoritized student populations. Informed by these findings, my third dissertation article, “A
Review,” uses a meta-narrative literature review methodology to review 60 studies that intersect
the domains of technology, leadership, and culturally responsive education and is the most
comprehensive review of literature to date that explicates a conceptual framework of technology
leadership for social justice. This manuscript advances research in educational leadership by
applying emergent methodologies to reveal new insights into (a) teacher technology use, (b)
school and district technology leadership, and (c) critical perspectives in technology leadership.

My dissertation has strong implications for research, theory, and practice in technology
leadership. Pertaining to research, this dissertation uses three current methodological approaches
to explicate similarities and differences within three different bodies of large-scale data on
teacher and leader technology use in schools. My first dissertation article is one of the first
educational technology research studies to use a three-step latent class analysis (LCA) approach,
a mixture modeling technique that has emerged in the educational leadership research within the
last decade, to investigate the extent to which there are different types of technology-using
teachers. My article provides clear guidance to educational technology researchers on how to
select model indicators and covariates from a nationally generalizable dataset and to employ
latent class analysis in order to find different statistically significant subgroups of survey responders. Building on the first dissertation article, my second dissertation article uses latent class analysis within a multilevel framework and is one of the first technology leadership studies to appropriately nest statewide data on teacher perceptions of technology leadership within two organizational levels and explore how teacher perceptions of technology leadership interact between the school and district levels. This article lays out how to structure large-scale datasets for multilevel analyses and how to manually specify a three-step multilevel latent class analysis (MLCA) with a cross-level interaction between the school and district levels, as well as two *post hoc* tests to estimate covariates and distal outcomes at each level. My third dissertation article describes a systematic, meta-narrative review methodology with the purpose of organizing and synthesizing a large corpus of research articles. My meta-narrative review outlines a six-stage process for identifying research questions, developing comprehensive search terms, utilizing content criteria to iteratively select relevant studies, mapping and coding conceptual, empirical, or thematic links between the studies, presenting the review findings within an organizing framework, and providing recommendations for future research in the area of interest that could facilitate more robust reviews of literature in technology leadership research.

My dissertation also has implications for the conceptual evolution of technology leadership within the larger body of educational leadership theories. Despite the fact that researchers have documented the evolution of educational leadership theories over time (Boyce & Bowers, 2018b; Hitt & Tucker, 2016; Wang, 2018; Wang & Bowers, 2016; Wang, Bowers, & Fikis, 2017), technology leadership remains on the periphery of the educational leadership landscape (Dexter, Richardson, & Nash, 2016; McLeod & Richardson, 2011; Richardson, Bathon, Flora, & Lewis, 2012; Richardson & Sterrett, 2018). While it is difficult to pinpoint one
reason why technology leadership is undervalued in the larger educational leadership research base, this dissertation seeks to address some of the longstanding theoretical and methodological assumptions to studying technology leadership and offers a different conceptual model for propelling the technology leadership field forward in understanding the connections between technology and emergent conceptions of teaching, learning, and leadership. My first dissertation article tackles the assumption that there is a monolithic conception of teacher technology use and outlines four different types of technology-using teachers. Rather than understanding teacher technology use on a continuum from good to bad, findings from this article support the notion that teachers use technology in multidimensional and complex ways. My second dissertation article attempts to investigate the assumption within the technology leadership literature that “technology leadership is essentially just good leadership” (Richardson, McLeod, & Sauers, 2015, p. 15) and is one of the first studies to align a statewide survey examining perceptions of technology leadership with empirically-validated surveys measuring perceptions of leadership for learning in order to investigate how teachers perceive technology leadership at the school and district levels and determine the extent to which these different perceptions are associated with student achievement outcomes. Although findings from this article support the notion that strong perceptions of technology leadership are associated with significantly higher student achievement outcomes, this article also finds that different perceptions of technology leadership are not a randomly occurring phenomenon, as teachers in historically minoritized schools are more likely to have lower perceptions of technology leadership and lower student achievement outcomes. This propels the notion that exploring technology leadership from the lens of social justice could help eliminate the perception gap in how teachers perceive technology leadership across increasingly diverse sets of schools and districts. Implications of my third article relate to
the application of more critical lenses in technology leadership research in order to address the social justice challenges that school leaders face in light of the new digital divide. My third dissertation article examines over sixty studies that intersect technology, leadership, and social justice and argues that school and district technology leaders must deeply understand the sociocultural influences of their schools in order to make more informed decisions about the technology they acquire to support their leadership and the values they espouse with teachers and the larger school community. This article lays out a new conceptual model that integrates distributional and relational approaches to social justice within technology leadership called *technology leadership for social justice*.

This dissertation also has implications for policy and practice for educational leaders. My first dissertation article provides a typology framework of teacher technology use that educational technology companies can use as they develop market strategies to design and sell new technologies for teachers. This article’s findings also can assist school and district leaders as they decide what technology to purchase and can help leaders design evidence-based professional learning experiences to push different types of teachers to use technology in new and innovative ways that ultimately support student learning. My second dissertation article has implications for school and district leaders, as well as state policy makers, as they design educational technology policy to improve instructional practice and to close achievement gaps. Extending decades of research findings that show that historically underserved schools and districts continue to face a digital divide in how teachers and students access and use technology resources (Normore & Lahera, 2018), findings from the second dissertation article also assert that there is also a *leadership* divide in Texas that facilitates the need for more holistic approaches that school and district leaders can adopt as they craft educational technology
policies that encourage school improvement with technology and eliminate educational inequalities between and within schools and districts. My third dissertation article introduces more critical perspectives in technology leadership research and provides a conceptual framework of technology leadership for social justice that technology leadership researchers and principal preparation programs can use to investigate leadership practice from a more contemporary lens and to more deeply understand the reciprocal influence of sociocultural contexts and leadership practice in order to cultivate excellent and equitable schools (Theoharis & Brooks, 2012).

Rather than using the standard dissertation structure, I decided to write my dissertation in the form of three independent articles for three reasons. First, it was important to me to maximize my contribution to the small subset of technology leadership research by writing three distinct articles that explore some aspect of technology leadership from a different perspective. Second, writing three distinct articles allowed me to examine the intersection of technology, leadership, and social justice at different organizational levels. I was able to examine large-scale data on technology leadership at the national and state policy levels and disaggregate the data to examine conceptual differences at the teacher, school, and district levels. I was also able to examine conceptual differences within the research literature on technology, leadership, and social justice. Third, using the three-article structure also allowed me to use three distinct, yet complementary methodologies, namely latent class analysis, multilevel latent class analysis, and meta-narrative review, in order to articulate a new empirical and conceptual model of technology leadership for social justice that could be a substantial contribution to technology leadership research.

The reminder of this introductory chapter will provide a general overview of the dissertation. I start by summarizing the research literature documenting the evolution of
technology leadership as a key leadership responsibility of modern-day school leaders, especially in light of the growing challenge of the digital divide in schools. Next, I explore the literature that explores technology and leadership through the lens of social justice. I then describe the use of typology subgroup analysis in educational leadership research and highlight its value in understanding the interaction of technology, leadership, and social justice. Last, I provide a brief summary of each of the three dissertation articles.

**School and District Technology Leadership**

Leaders will always be consequential forces in schools. This fact is strongly supported by thirty years of educational leadership research that finds that effective principals, only second to classroom teachers, positively influence student achievement outcomes (Bowers & White, 2014; Coelli & Green, 2012; Day, Du, & Sammons, 2016; Hallinger, 1992; Hallinger & Heck, 1996, 2010; Hallinger & Murphy, 1985; Leithwood, Harris, & Hopkins, 2008; Robinson, Lloyd, & Rowe, 2008; Seashore Lewis, Leithwood, Wahlstrom, & Anderson, 2010; Sebastian & Allensworth, 2012; Sebastian, Huang, & Allensworth, 2017) and that district central office administrators can have a strong effect on student achievement outcomes at the student, school, and district levels as well (Bowers, 2008, 2010b, 2015; Bowers, Ni, & Esswein, 2018; Darling-Hammond et al., 2005; Elmore, 1993; Honig, 2008, 2012; Leithwood, 2010; McLaughlin & Talbert, 2003; Snipes, Doolittle, & Herlihy, 2002). Still, although we understand that leaders are imperative to meaningful school improvement, it is important to realize that leadership does not exist in a vacuum (Hallinger & Heck, 2011; Hallinger & Leithwood, 1998; Hallinger & Murphy, 1986). Understanding the school and larger social culture in which leaders indirectly influence teaching and learning (Dancy & Horsford, 2010; Driscoll & Goldring, 2005; Jean-Marie, Normore, & Brooks, 2009), as well as the tools and contexts that shape leadership behaviors that
are connected to student achievement (Marks & Printy, 2003; Murphy, Elliott, Goldring, & Porter, 2007; Robinson et al., 2008; Urick, 2016; Urick & Bowers, 2014), should be a new frontier for educational leadership research.

Recently, policy makers and educators have pressed that educational technology could be a powerful tool to support school improvement in the digital age (U.S. Department of Education, 2017). Many advocates of educational technology believe that digital tools are the key to providing high-quality educational experiences for all students and insist that technology can cultivate positive changes in instruction that boost achievement and better prepare students for the demands of modern work and life (U.S. Department of Education, 2010, 2016, 2017). In reaction to the growing amount of technology in schools, technology leadership has emerged as an important role that administrators must adopt in reaction to the push to integrate technology in classrooms (Anderson & Dexter, 2005; Dexter, 2011; Flanagan & Jacobson, 2003; Kearsley & Lynch, 1992; McLeod & Richardson, 2013; Schrum & Levin, 2016; Thomas & Knezek, 1991). One of the most prominent technology leadership frameworks, the ISTE (2009) NETS-A Standards, outlines five key roles for technology leaders in schools: (1) equity and citizenship advocate, (2) visionary planner, (3) empowering leader, (4) systems designer, and (5) connected learner (Crompton, 2014; Richardson et al., 2012). In general, these frameworks espouse that effective technology leaders create equitable systems of support through the human and material resources they purchase in order to help educators utilize technology in ways that promote knowledge construction, higher-order thinking, and collaborative learning (Flanagan & Jacobson, 2003; McLeod & Richardson, 2013; Scardamalia & Beretier, 2007; Schrum & Levin, 2016). When leaders focus their instructional leadership efforts on these technology leadership behaviors, research finds that effective technology leadership is the key to positive technology-
related outcomes (Anderson & Dexter, 2005) and is associated with higher perceptions of leadership effectiveness (Weng & Tang, 2014). In order to support leaders as they venture into this emerging leadership practice, researchers have simply posited that “technology leadership is essentially just good leadership for our digital era” (Richardson et al., 2015, p. 15).

However, recent research has offered three reasons why positioning technology leadership as just good leadership is not as simple as leaders, researchers, and policy makers once thought. The first reason is that critics of educational technology have long documented how the rhetoric surrounding the promise of technology to improve schools has not necessarily spawned lasting changes in teacher pedagogy and student achievement growth across schools and districts (Cuban, 2001, 2018; Cuban, Kirkpatrick, & Peck, 2001; Sanders & George, 2017; Zhao, Zhang, Lei, & Qiu, 2016). In turn, this “rhetoric-reality gap” (Sanders & George, 2017, p. 3) has left school and district leaders with many lingering questions about the return on their investment in technology (Cuban, 2018). My first dissertation article attempts to establish a baseline in understanding how teachers use technology in order to bring greater clarity to school leaders as they create support systems for teachers to use technology in more meaningful ways.

Second, despite the popularity of the ISTE (2009) NETS-A leadership framework as a guide to assist school and district administrators in their technology leadership roles, research has found that school and district leaders still struggle with the unique challenges of instructional leadership with technology (English, Papa, Mullen, & Creighton, 2012; Richardson et al., 2015; Sauers, Richardson, & McLeod, 2014; Schwanenberger et al., 2013). Further, as the ISTE (2009) NETS-A framework does not necessarily provide guidance on what order to perform the behaviors or how leaders can adjust the behaviors based on their school contexts, there is a distinct need for more research studies within the technology leadership literature that offer
substantive and practical theories of action to guide school and district leaders (Dexter et al., 2016; McLeod & Richardson, 2011; Richardson & Sterrett, 2018; Sauers et al., 2014). My third dissertation article builds on the findings from the first two articles and reviews the technology leadership literature through a different theoretical lens in order to elicit new insights into how to support school leaders with new challenges of technology leadership.

The third reason why it might be problematic to assert that technology leadership is just good leadership is that leaders in historically minoritized communities continue to face systemic obstacles related to a digital divide that prevent them from cultivating the vision for technology leadership that they aspire to accomplish (Eamon, 2004; Gorski, 2009; Normore & Lahera, 2018; Valadez & Duran, 2007; Vigdor, Ladd, & Martinez, 2014; Warschauer, 2016; Warschauer, Knobel, & Stone, 2004; Warschauer & Matuchniak, 2010). Recent research has highlighted the importance of investigating how teachers and leaders perceive leadership practice across different contexts with large-scale data (Boyce & Bowers, 2018a; Goff, Goldring, & Bickman, 2014; Hallinger & Heck, 2011; Heck & Hallinger, 2009; Urick & Bowers, in press). Yet, research in technology leadership tends to primarily offer descriptive research on exemplary technology-using school and districts (Levin & Schrum, 2012, 2013, 2014; Sauers et al., 2014). My second dissertation article begins to address this gap in the literature by examining teacher perceptions of technology leadership with large-scale statewide data, while my third dissertation article explicates a new theoretical model of technology leadership that can guide leaders in future practice. To this end, as these tensions materialize in reaction to the increasing quantity and use of technology in schools, technology leadership research must evolve to help leaders across increasingly diverse schools and districts surmount the unique challenges of digital age leadership for school improvement.
The Need for Critical Perspectives in Technology Leadership

Recently, policy makers and school reformers have tried to assist school and district leaders to become better instructional leaders who leverage technology to improve student outcomes. However, the changing social and cultural contexts of today’s schools have complicated efforts to provide one solution to educational reform and has created a cultural and educational mismatch between students in schools and educational leaders and policy makers (Deschenes, Cuban, & Tyack, 2001; Horsford, Grosland, & Gunn, 2011; Khalifa, Gooden, & Davis, 2016). In order to address this issue, instead of developing solutions to address this mismatch by minimizing the achievement gap (Scheurich et al., 2017), Venzan Chambers (2009) argues that leaders should address this disparity as a “receivement gap” (p. 418), purposefully developing policies that eliminate the larger systemic and structural barriers that impact the “educational inputs – what the students receive on their educational journey” (p. 418). With this reconceptualization of the achievement gap as a receivement gap, school leaders now have a moral authority to provide the proper and equitable organizational supports and structures that provide educational opportunities for all students (Bates, 2006; Bogotch, 2000; Furman, 2004; Furman & Shields, 2005; Greenfield, 2004; Hallinger & Leithwood, 1998). In the last decade, there been a rise of critical research in the educational leadership literature that seeks to explain how leaders can employ culturally responsive leadership approaches to champion social justice and to eliminate deeper structural and systemic inequalities within historically minoritized communities through their leadership efforts (Khalifa et al., 2016).

The social justice leadership research literature explores notions of social justice in schools within two dimensions: distributional and relational (Gewirtz, 2001; Horsford, 2016; North, 2006). While the distributional notion of social justice argues for the equal distribution of
school resources across all schools, the *relational* notion of social justice pertains to understanding how individuals interact with each other, as well as outside sociocultural factors that influence the structures and systems that govern how individuals live and relate to each other (Gewirtz, 2001; Horsford, 2016; North, 2006). As a way to promote social justice in schools, culturally responsive leadership has emerged as a key leadership framework that engenders leadership for social justice as an “action-based approach to creating school contexts and curriculum that responds to the educational, social, political, and cultural needs of students” (Khalifa et al., 2016, p. 7). Culturally responsive leadership requires school leaders to reflect on their own personal biases, model teaching and leadership practices that are culturally relevant to their schools, leverage resources to intentionally cultivate a welcoming school community, and learn to comprehend, engage, and advocate for issues that are important to the school community (Khalifa et al., 2016, p. 7). With an intent focus on social justice and culturally responsive leadership, research has shown that leaders can boost student engagement and student achievement outcomes (Bustamante, Nelson, & Onweugbuzie, 2009; Deal & Peterson, 1999; Khalifa, 2012; Madhlangobe & Gordon, 2012; Riehl, 2000).

Similarly, the educational technology literature has also grappled with distributional and relational aspects of social justice related to the digital divide in schools. Pertaining to the equal distribution of resources, research on the digital divide examines the distributional consequences of digital inequality on three levels (Attewell, 2001; Gorski, 2005; van Deursen, Helsper, Eynon, & van Dijk, 2017). First-level digital divide research in schools is concerned with disparities in access to computers and the Internet across demographic subgroups (Judge, Puckett, & Bell, 2006; Purcell, Heaps, Buchanan, & Friedrich, 2013). Second-level digital divide research examine differences in the skills and knowledge that individuals have to use the technology and
the motivations that govern particular patterns of usage (Kopcha, 2012; Lei & Zhao, 2007; Tondeur, van Braak, Ertmer, & Ottenbreit-Leftwich, 2017). Third-level digital divide research explores the extent to which technologies perpetuate social norms related to certain social identifiers, like race (Mou & Peng, 2009; Solomon & Allen, 2002), gender (Porter, Lee, Simon, & Guzdial, 2017), socioeconomic class (Digital Promise, 2014), and ability (Dobransky & Hargittai, 2006), and how these norms reinforce biases and systemic constructs that were set up to limit technology access and unfairly impact certain school outcomes (Gorski, 2008; van Deursen et al., 2017). My first and second dissertation articles provide generalizable evidence from national and state-level data that these issues of equity and access still exist in today’s schools. Similarly, through a relational social justice paradigm, several studies have found that technology can have an emancipatory effect on students’ experience in the classroom when educators use technology in ways that encourage participation and use pedagogies that validate and respect students’ cultural identities in relation to how they make meaning of content through digitally-mediated classroom experiences (Eglash, Gilbert, Taylor, & Geier, 2013; Jenkins et al., 2009; Sefton-Green, 2006). My third dissertation article uses a culturally responsive lens to examine technology leadership practice and offers ways that principal preparation programs can help school leaders understand the importance of using cultural responsiveness as a way to boost student achievement and teacher engagement.

While educational leadership and instructional technology researchers have used critical lenses to examine culturally responsive leadership and technology use in schools in isolation, there are limited studies that use critical perspectives to examine technology and leadership together through a social justice lens. In recent literature reviews examining technology leadership research on the five tenets of the ISTE (2009) NETS-A Standards, several authors
have noted that the standard on how technology leaders act as equity advocates is under researched in the technology leadership literature base (Anderson & Dexter, 2005; McLeod & Richardson, 2011; Richardson et al., 2012). In light of the varied social justice challenges that leaders face with technology leadership, exploring the intersection of technology, leadership, and social justice could provide the missing link to investigating how leaders enact technology leadership across diverse school contexts and provide a much needed theoretical framing for understanding how leaders can adapt their technology leadership to address the cultural needs of students and teachers within their school communities. My third dissertation article addresses this issue by using an equity-oriented framework to interrogate the body of literature intersecting technology, leadership, and social justice.

**Typology Subgroup Analysis**

Investigating this new conception of leadership, technology, and social justice requires the use of new methodological approaches to more deeply understand the interaction of leadership practice with the organizational and cultural context of schools. Past quantitative research in educational leadership has used large-scale data to identify the specific leadership styles and behaviors that are associated with positive student achievement outcomes (Hallinger, 1992; Hallinger & Heck, 1996, 1998; Hallinger & Murphy, 1985; Leithwood, 1992; Robinson et al., 2008). However, as it became clear that leaders employ multiple leadership styles depending on their school contexts (Day et al., 2016; Marks & Printy, 2003; Printy, Marks, & Bowers, 2009; Urick & Bowers, 2014), research shifted to using more comparative measures to understand the different ways that leaders enact leadership behaviors according to their school environments (Bowers et al., 2017; Boyce & Bowers, 2018a; Marks & Printy, 2003; Printy et al., 2009; Sebastian et al., in press; Tan, 2018; Urick, 2016; Urick & Bowers, 2014; Urick &
Typology subgroup analysis has emerged in the larger educational leadership literature as a robust methodological approach that uses large-scale data and statistical analyses to understand how perceptions of leadership differ across different school contexts and organizational levels (Agasisti, Bowers, & Soncin, in press; Bowers et al., 2017; Boyce & Bowers, 2016; Sebastian et al., in press; Urick, 2016; Urick & Bowers, 2014). As opposed to variable-centered methods that regress survey data to a single best fit line or that simply determine relationships between leadership behaviors absent of any context, typology subgroup analysis is a person-centered statistical method that identifies subgroups of individuals based on how their perceptions align or differ from each other (Bowers et al., 2017; Urick, 2016).

Educational leadership researchers have commonly used two approaches to typology subgroup analysis, either cluster analysis or latent class analysis (Bowers, 2010a; Goldring, Huff, May, & Camburn, 2008; Vermunt & Magidson, 2002). Latent class analysis (LCA) has several key advantages over cluster analysis, including the use of hypothesis tests to determine different statistically significant subgroups of survey responses, the presence of fit statistics to determine model fit, and the inclusion of covariates and distal outcomes within an omnibus model to examine how contextual variables are associated with group membership across the different subgroups (Collins & Lanza, 2010; Jung & Wickrama, 2008; Masyn, 2013; Muthén & Asparouhov, 2002; Nylund, Asparouhov, & Muthén, 2007; Nylund-Gibson & Masyn, 2016; Samuelsen & Raczynski, 2013; Vermunt & Magidson, 2002; Vermunt & Magidson, 2004). My first dissertation article employs a three-step latent class analysis to determine the extent to which there are different types of technology-using teachers and what demographic variables are associated with group membership. Additionally, the complexities of leadership practice require researchers to use multilevel models that appropriately nest teachers in schools and districts.
order to understand how individuals or collective bodies of individuals perceive leadership differently (Bellibas & Liu, 2017; Boyce & Bowers, 2018a; Hallinger & Heck, 2011; Urick & Bowers, in press). Another advantage that latent class analysis has over cluster analysis is that researchers can utilize latent class analysis within a multilevel framework. In general, multilevel latent class analysis (MLCA) estimates how subgroups of responders on one level, usually the school-level, influence subgroups of survey responses at a second level, like the district-level (Asparouhov & Muthén, 2008; Finch & French, 2014; Henry & Muthén, 2010; Vermunt, 2003, 2008). The MLCA model also allows for researchers to manually specify covariates and distal outcomes to examine differences in subgroup assignment across different demographic and community contexts (Asparouhov, 2018). My second dissertation article investigates subgroups of teacher perceptions of technology leadership at the school and district levels and argues that different perceptions, ranging from high to low, are associated with particular demographic groups. In all, typology subgroup analysis, and in particular latent class analysis (LCA), allows researchers to understand variations of leadership practice through the individual or collective perceptions of teachers or leaders, while also taking into account the social, cultural, and organizational contexts that might influence perceptions of leadership practice.

Article One

“Toward a Typology of Technology-Using Teachers: A Three-Step Latent Class Analysis (LCA) of the NCES Teachers’ Use of Educational Technology in U.S. Public Schools, 2009 (FRSS 95)”

The purpose of my first dissertation article is to determine the extent to which there is a typology of technology-using teachers using a nationally generalizable dataset, the Fast Response Survey System Teachers’ Use of Educational Technology in U.S. Public Schools,
2009 (FRSS 95) from the National Center for Education Statistics (NCES). Leaders and policy makers have heavily invested in the promise of educational technology to help improve teacher pedagogy and boost student achievement (U.S. Department of Education, 2014, 2016, 2017). However, despite the rising amount of technology entering schools and districts, several critics have argued that this investment in technology has not produced substantive results (Bulman & Fairlie, 2016; Cuban, 2001, 2015, 2018; Sanders & George, 2017), especially in historically minoritized communities where digital divides are widespread (Gorski, 2002, 2005, 2009; Normore & Lahera, 2018; Warschauer, 2016; Warschauer et al., 2004; Warschauer & Matuchniak, 2010). Past research has attempted to understand teacher technology use in schools by outlining the specific ways that teachers use technology (Bebell, Russell, & O'Dwyer, 2004; O'Dwyer, Russell, & Bebell, 2004, 2005; Russell, Bebell, O'Dwyer, & O'Connor, 2003; Russell, O'Dwyer, Bebell, & Tau, 2007) or by understanding the factors pertaining to why some teachers use more technology than others (An & Reigeluth, 2011; Ertmer, 1999; Kopcha, 2012). Most of the research examining how and why teachers use technology explore these two perspectives in isolation. Yet, combining these perspectives into a third perspective – what types of teachers use technology – could provide additional insights into teacher technology use in schools.

The Rogers (1962) innovation adoption model was one of the first known typologies of technology users and organized technology users into five categories: innovators, early adopters, early majority, late majority, and laggards. While innovators, early adopters, and the early majority subgroups usually adopt technology quickly without any hesitation, users in the late majority and laggards subgroups tend to adopt new technologies at a slower pace. Specifically pertaining to schools, the Rogers (1962) study spawned other typologies that examined the usage patterns of technology-using teachers. After interviewing several educators in Ireland, Donnelly,
McGarr, and O'Reilly (2011) find four subgroups of technology-using teachers, namely the *contented traditionalist*, the *selective adopter*, the *inadvertent user*, and the *creative adapter*. Likewise, in a case study of teachers in Cyprus, Mama and Hennessy (2013) describe a four-group typology of technology-using teachers based on teacher attitudes. Both the Donnelly et al. (2011) and Mama and Hennessy (2013) describe a typology of four, mutually exclusive subgroups of technology-using teachers within a single school setting in an ordinal solution from low to high. However, my first dissertation article is the first study to determine the extent to which there are different subgroups of technology-using teachers using nationally generalizable data on teacher technology use in U.S. public schools.

The research questions for this study were: (1) Using a nationally representative dataset, to what extent are there different types of teachers who use technology? (2) To what extent are other contextual factors, such as urbanicity, percentage of students on free/reduced lunch, total number of classroom computers, school type, years of teaching experience, and enrollment, associated with membership in these subgroups of technology-using teachers?

I analyzed survey data on teacher technology use available from the NCES Fast Response Survey System Teachers’ Use of Educational Technology in U.S. Public Schools, 2009 (FRSS 95). My study examined a subset of the dataset and had a sample size of \(n=2,764\) teachers who indicated that they use technology in the classroom. Weights were applied to the sample size so that the findings were generalizable to all 2.39 million public school teachers in the United States in 2009 (National Center for Education Statistics, 2009). I used a three-step latent class analysis (LCA) framework (Collins & Lanza, 2010; Jung & Wickrama, 2008; Masyn, 2013; Muthén & Asparouhov, 2002; Nylund et al., 2007; Nylund-Gibson & Masyn, 2016; Samuelsen & Raczynski, 2013; Vermunt & Magidson, 2002; Vermunt & Magidson, 2004) in order to
understand how and why different teachers use technology and to identify different statistically significant subgroups of technology-using teachers. In addition, I was also able to include covariates in the analytic model to see how different demographic contexts were associated with teacher membership in the subgroups of technology-using teachers.

My results indicated that there were four different statistically significant subgroups of technology-using teachers: *Dexterous* (24.4%), *Presenters* (24.8%), *Assessors* (28.4%), and *Evaders* (22.2%). Teachers in the *Dexterous* subgroup use technology fluidly and had the highest overall satisfaction with technology professional development. In contrast, teachers in the *Evaders* subgroup barely use technology in their classrooms or for productivity tasks, like managing student records or emailing parents, and had the lowest overall satisfaction with technology professional development. Interestingly, two subgroups were associated with specific pedagogical techniques with technology. Teachers in the *Presenters* subgroup reported that they use technology to create classroom presentations and also instruct their students to make presentations as well. Finally, teachers in the largest subgroup, the *Assessors* subgroup, report that they use technology to prepare drill and practice activities for students and use technology to teach basic skills. My results also find that elementary school teachers are also more likely to be in the *Evaders or Assessors* subgroup than in the *Dexterous* subgroup. Teachers in schools with the majority of students on free and reduced lunch were more likely to be in the *Assessors* subgroup than the *Dexterous* subgroup. Additionally, as the number of computers increased, teachers were less likely to be in *Assessors or Presenters* subgroup than in the *Dexterous* subgroup.

Results of this study show that teachers use technology in multidimensional ways and that the variance across the different types of technology-using teachers is not a random
occurrence. Rather, teachers in low-income schools are more likely to use technology in didactic ways that are disconnected from best practices with technology. My study has strong implications for how leaders evaluate new digital tools, design professional learning experiences for teachers, and develop technology policies that address disparities in how teachers access and use technology in the classroom. As one example, the typology outlined in this study could be a mechanism that school and districts use to provide evidence-based, highly personalized technology professional development for teachers (Agasisti et al., in press; Bowers, Shoho, & Barnett, 2014; Halverson, 2014). This study also has implications for policy makers to develop backward-mapped educational policies that consider the needs of teachers at the ground level of implementation in order to address the longstanding consequences of a digital divide in schools (Culp, Honey, & Mandinach, 2003; Elmore, 1980).

**Article Two**

“Is School and District Technology Leadership ‘Just Good Leadership’: A Multilevel Latent Class Analysis (MLCA) of the 2011-12 Texas School Technology and Readiness (STaR) Charts”

The purpose of this study to investigate leadership at the school and district levels from a new conceptual and empirical lens by examining perceptions of technology leadership from statewide data in the 2011-12 Texas School Technology and Readiness (STaR) Charts. Early frameworks in technology leadership focused on developing the technical competencies of school leaders in order to improve schools (Bozeman & Spuck, 1991; Kearsley, 1988; Kearsley & Lynch, 1992; Thomas & Knezek, 1991). As researchers realized that school improvement with technology required leaders to adopt a more holistic approach to technology leadership, new frameworks, like the ISTE (2009) NETS-A Standards, began to mirror prominent theories in
educational leadership, like transformational leadership (Bass & Avolio, 1990, 1993; Hallinger, 1992; Leithwood, 1992; Leithwood & Sun, 2012) and shared instructional leadership (Marks & Printy, 2003; Printy et al., 2009; Robinson et al., 2008). Consequently, as the ISTE (2009) NETS-A technology framework emerged as one of the most widely used technology leadership frameworks (Anderson & Dexter, 2005; Crompton, 2014; Gibson, 2002; McLeod & Richardson, 2011; Richardson et al., 2012; Yu & Durrington, 2006), an assumption also emerged within the larger literature base that technology leadership is just good leadership (Richardson et al., 2015).

Still, there are several unanswered tensions within the technology leadership literature that researchers have yet to fully resolve. Recent investigations of the technology leadership literature find that technology leadership is understudied by educational leadership researchers (Dexter et al., 2016; McLeod & Richardson, 2011; Richardson et al., 2012; Richardson & Sterrett, 2018). Further, even within the small subset of research that does exist, technology leadership studies do not offer substantive theories of action that are generalizable across diverse school and districts (McLeod & Richardson, 2011; Sauers et al., 2014). The lack of nationally generalizable data on technology leadership could be one factor that has contributed to these theoretical and methodological shortcomings. However, my dissertation is one of the first educational leadership studies to use statewide data from the School Technology and Readiness (STaR) Charts to examine technology leadership practices in the state of Texas.

Originally released in 1997, the report on the first national administration of the School Technology and Readiness (STaR) Charts survey outlines educators’ perceptions of technology in four dimensions, namely hardware, software, connectivity, and digital content, and finds four types of schools in their typology based on these technology indicators (CEO Forum on Education and Technology, 1997). Future iterations of the STaR Charts in states, like Texas,
included indicator variables that are related to technology leadership, like leadership and vision, budget, collaboration and communication, and instructional support (Texas Education Agency, 2014). The Texas STaR Charts are a useful survey tool to study teachers’ perceptions of technology leadership in that it aligns closely with recent empirically-validated leadership surveys, like the Comprehensive Assessment of Leadership for Learning (CALL) survey developed by the University of Wisconsin-Madison (Blitz, Salisbury, & Kelley, 2014; Bowers et al., 2017; Halverson, Kelley, & Shaw, 2014; Kelley & Halverson, 2012). Further, similarly to the CALL survey, the STaR Chart survey collects individual teacher perceptions of technology leadership on four domains, Teaching and Learning (TL), Educator Preparation and Development (EP), Leadership, Administration, and Instructional Support (L), and Infrastructure for Technology (INT), and then aggregates the data to the school and district levels (Texas Education Agency, 2014). My dissertation is one of the first educational leadership studies to analyze the STaR Chart data using typology subgroup analysis within a multilevel framework to investigate the interaction of leadership and technology on multiple organizational levels.

The research questions for this study were: (1) To what extent are there significantly different subgroups of aggregate, school-level teacher responses to the 2011-12 Texas School Technology and Readiness (STaR) Chart surveys? (2) To what extent are school-level variables, such as urbanicity, school type, enrollment, proportion of African-American and Hispanic students, proportion of economically disadvantaged students, student-teacher ratio, and years of teaching experience, associated with group membership in the school subgroups? (3) To what extent do the mean percentage pass rates on the 2012 Texas STARR/TEKS standardized tests vary across different types of schools, after controlling for the covariates? (4) To what extent do
the subgroups of aggregate, school-level teacher responses to the 2011-12 Texas *School Technology and Readiness (STaR)* Chart survey distribute across different types of districts? (5) To what extent are district-level variables, such as urbancity, enrollment, proportion of African-American and Hispanic students, proportion of economically disadvantaged students, percent of special education students, average years of teacher experience, instructional expenditures per pupil, expenditures on instructional equipment, and expenditures on instructional staff, associated with membership in the district subgroups? (6) To what extent do the mean percentage pass rates on the 2012 Texas STARR/TEKS standardized tests vary across different types of districts, after controlling for the covariates?

I analyzed data from the 2011-12 Texas *School Technology and Readiness: A Teacher Tool for Planning and Self-Assessment (STaR)* surveys, as well as public use data from the Texas Education Agency and the Common Core of Data available through the National Center for Education Statistics (NCES). My study had a final sample size of \( n = 6,935 \) schools in \( n = 910 \) districts in Texas. As an extension of latent class analysis (LCA) that finds different statistically significant subgroups of survey responses, in this study, I used multilevel latent class analysis (MLCA) in order to better understand the complexity of leadership practice by appropriately nesting teachers in schools and districts (Hallinger & Heck, 2011; Hox, 2002; Raudenbush & Bryk, 2002). This study was anchored in past multilevel latent class analysis research that has examined the alignment of instructional leadership perceptions between teachers and leaders, as well as between individual teachers and collective bodies of teachers (Bellibas & Liu, 2017; Boyce & Bowers, 2018a; Hallinger & Heck, 2011; Urick & Bowers, in press). Multilevel latent class analysis (MLCA) is useful in determining whether different subgroups of responders exist at one level, like the school-level, and how these subgroups distribute across different
statistically subgroups of responders at a higher level, like the district (Asparouhov & Muthén, 2008; Finch & French, 2014; Henry & Muthén, 2010; Vermunt, 2003, 2008). Researchers can also manually specify demographic and context variables as covariates and distal outcomes, like student achievement scores (Asparouhov, 2018). I used multilevel latent class analysis to determine the extent to which there are different subgroups of teacher responders to the STaR Charts at the school level and how, if at all, these school-level subgroups are distributed across different statistically significant subgroups of responders at the district level. I also analyzed several school and district demographic, community, and context variables as covariates and used analysis of covariance (ANCOVA) statistical procedure to determine whether there are statistically significant differences in the aggregated school and district student percent pass rates on the 2012 State of Texas Assessment of Academic Readiness (STARR) and Texas Essential Skills and Knowledge (TEKS) achievement tests across the school and district subgroups.

My results indicated that there were three statistically significant subgroups of teacher responses to the STaR Charts at the school level in Texas. The school-level typology was normally distributed in an ordinal solution of High STaR Schools (29.4%), Moderate STaR Schools (42.3%), and Low STaR Schools (28.2%). Teachers in the High STaR Schools subgroup report strong use of technology and strong leadership, while teachers in the Moderate STaR Schools and the Low STaR Schools subgroups report lower perceptions of teacher involvement in professional development and instructional support for technology. Internet connectivity was consistently high across the three subgroups. Pertaining to the context variables as covariates, I also found that schools from towns and rural communities are more likely to be in the Moderate STaR Schools subgroup than in the High STaR Schools subtype and that large schools are more likely to be in the Low STaR Schools subgroup than in the High STaR Schools subtype when
compared to smaller schools. I also found that certain community and demographic variables were associated with group membership. Teachers in schools with higher proportions of special education and economically disadvantaged students are more likely to be in the Low STaR Schools subgroup than in the High STaR Schools subgroup. I also found that the school-level typology has a significant independent effect on student achievement in Texas, explaining 2% of the variance in school-level pass rates on the 2012 Texas STARR/TEKS assessments. My findings also indicated that High STaR Schools had statistically significantly higher pass rates on the 2012 Texas STARR/TEKS assessments, when controlling for the covariates.

I also found four different statistically significant district subgroups of teacher STaR Chart responders in a normally distributed, ordinal solution as well, namely Model STaR Districts (19.8%), High STaR Districts (22.9%), Moderate STaR Districts (50.1%), and Low STaR Districts (22.6%). There was an uneven distribution of the school-level subgroups across the district-level subgroups with the Model STaR Districts and High STaR Districts subgroups containing most of the teachers in the High STaR Schools subgroup, while the Moderate STaR Districts and Low STaR Districts subgroups contained most of the teachers from the Moderate STaR Schools and Low STaR Schools subgroups. I found that large school districts were more likely to be in the High STaR Districts subgroup than in the Low STaR Districts subgroup. I also found that students’ racial background was associated with membership in the district-level subgroups, as African-American and Hispanic students were less likely to be in the Model STaR Districts subgroup than in the Low STaR Districts subgroup. Additionally, I found that the district-level subgroups also had an independent effect on district student achievement pass rates, explaining 9.3% of the variance in district percent pass rates on the 2012 Texas STARR/TEKS.
assessment. I also found that Low STaR Districts had significantly lower pass rates on the 2012 Texas STARR/TEKS standardized achievement tests, when controlling for the covariates.

My findings align with the original 1997 STaR Report released over twenty years ago that found four different types of responders to the STaR Chart survey in an ordinal solution. With the addition of the leadership variables in the Texas STaR Charts, my findings speak to research findings in the larger educational leadership literature that argue that teachers’ perceptions of leadership are isomorphic between level 1, the individual level, and level 2, the collective level (Urick & Bowers, in press), indicating that teachers in Texas might have a unidimensional perception of technology leadership as the specific behaviors that principals enact rather than understanding technology leadership as the combination of individual action and the organizational context that influences leadership practice (Boyce & Bowers, 2018b; Hallinger, 2011; Marks & Printy, 2003; Printy et al., 2009; Spillane, Halverson, & Diamond, 2001, 2004). My findings also provide the first generalizable evidence from large-scale data from Texas that technology leadership is just good leadership, as the three school-level typology and the four district-level typology has an independent effect on student achievement and that higher perceptions of technology are associated with statistically significantly higher student pass rates on the 2012 Texas STARR/TEKS standardized assessments. However, my results also suggest that the variance in teachers’ perceptions of technology leadership is not a randomly occurring phenomenon, as teachers within the school-level and district-level subgroups with the lowest perceptions of technology leadership and the lowest student achievement outcomes are more likely to serve higher proportions of students from historically minoritized backgrounds.

The findings from this study have strong implications for the use and development of empirically validated measures of technology leadership that seek to understand how teachers
and leaders’ perceptions of technology leadership align or differ. My findings also have implications for policy makers as they design educational technology policy aimed at eliminating educational inequality with technology and pushes researchers, leaders, and policy makers to approach digital social justice as a distributional and relational construct that not only provides technology resources for schools, but also supports leaders in developing approaches to technology leadership that are contextually relevant. For example, utilizing equity audits as a tool to evaluate technology policy aimed at bridging digital divides and improve teacher and leader practice with technology could provide a more complete picture for school leaders and policy makers as they design more equitable instructional interventions (Skrla, McKenzie, & Scheurich, 2009).

Article Three

The purpose of my third dissertation article is to conduct a systematic review of literature in order to summarize and synthesize the extant literature that intersects the domains of technology, leadership, and culturally responsive leadership to inform a new integrated leadership framework called technology leadership for social justice. Over the last two decades, there has been renewed interest in understanding the role that school leaders play in technology-focused instructional reform (Beytekin, 2014; Dexter, 2008; Kearsley & Lynch, 1992; McLeod, Richardson, & Sauers, 2015; Thomas & Knezek, 1991). While the majority of literature on school and district technology leadership attempts to understand the behaviors associated with positive technology-related outcomes in schools (Dexter, 2008; Dexter et al., 2016; Richardson et al., 2012; Richardson & Sterrett, 2018), issues related to the digital divide continue to
complicate leadership efforts with technology (Gorski, 2002, 2005, 2008; Normore & Lahera, 2018; Warschauer, 2016). Researchers have pressed that there is a distinct need for more critical frameworks to examine the body of technology leadership literature (Collins & Halverson, 2018; English et al., 2012; Schwanenberger et al., 2013).

Culturally responsive leadership is a leadership framework that ensures that leaders create systems that address the cultural needs of all students (Khalifa et al., 2016). As an subset of culturally responsive leadership, Theoharis and Brooks (2012) offer an equity-focused instructional leadership framework that seeks to understand differences in access, process, and outcomes across the content areas. Access refers to the strategies that leaders employ to provide high-quality content and instruction to all students (Theoharis & Brooks, 2012). Process speaks to the ways in which leaders establish democratic and collaborative procedures with other teachers and leaders to acquire instructional resources (Theoharis & Brooks, 2012). Outcomes refers to the various methods and measures that leaders use to determine instructional and leadership effectiveness within their school (Theoharis & Brooks, 2012). My third dissertation article offers one of the first critical analyses of the technology leadership literature by applying the Theoharis and Brooks (2012) framework to better understand the intersection of technology, leadership, and social justice. My study starts with a body of 3,438 studies intersecting technology, leadership, and social justice and iteratively narrows these studies down into the 60 articles used as the dataset for this study.

The research questions for this study were: (1) To what extent can major themes and relationships be identified within the selected body of literature focused on leadership, educational technology, and culturally responsive leadership approaches? (2) To what extent can
these themes be integrated into a single conceptual model? (3) What are the theoretical, practical, and policy implications for an integrated framework of technology leadership for social justice?

I used an exploratory, meta-narrative literature review methodology that systematically organizes and synthesizes a body of literature in order to uncover deeper conceptual and theoretical connections within complex domains of literature (Goodwin & Geddes, 2004; Gough, Oliver, & Thomas, 2012; Greenhalgh et al., 2009; Greenhalgh et al., 2004, 2005a; Hallinger, 2013; Wong et al., 2013). In light of recent calls for more robust reviews of literature in educational leadership that are systematic, reproducible, and comprehensive (Boyce & Bowers, 2018b; Hallinger, 2013), the meta-narrative review methodology was the best method to utilize for this study as it provides a way to synthesize a body of literature and identify “intellectual dry holes” (Hallinger, 2013, p. 127) through a six-phase process for selecting relevant literature based on the research question at hand. This six-stage process included the planning stage, the search stage, the mapping stage, the appraisal stage, the synthesis stage, and the recommendations stage (Boyce & Bowers, 2018b; Greenhalgh et al., 2009; Greenhalgh et al., 2005b). My third dissertation article outlines each stage and organizes the findings based on the Theoharis and Brooks (2012) leadership framework of access, process, and outcomes.

I found three themes within the literature base within the 60 studies intersecting technology, leadership, and social justice: resource control, distributed leadership, and sociocultural influences. The combination of these three themes informed a new conceptual framework of technology leadership for social justice that could guide school leaders in distributing their technology leadership efforts through the material and human resources they acquire in ways that consider the sociocultural influences within their school contexts.
Findings from my third dissertation article offer one of the first critical analyses of the technology leadership literature through the lens of cultural responsiveness and social justice. My study pushes the need for more criticality within the larger technology leadership literature to combat the notion that technology is a neutral tool that is disconnected from larger cultural and societal norms (Bradshaw, 2017; Kruger-Ross, 2013; Subramony, 2017; Webster, 2017). My review of literature also speaks to the lack of research studies examining the link between technology leadership and student achievement, especially as technology leadership is closely related to shared instructional leadership (Marks & Printy, 2003; Printy et al., 2009; Robinson et al., 2008) and leadership for learning (Boyce & Bowers, 2018b; Hallinger, 2011; Hallinger & Heck, 2010; Murphy et al., 2007) that looks to connect leadership practice with student achievement. In light of the challenges that leaders face to use technology to bridge educational and digital divides, my review speaks to the need for more robust research that investigates the connection between culture, technology, leadership, teaching, and student outcomes.

**Intellectual, Practical, and Personal Goals**

My dissertation is informed by several intellectual, practical, and personal goals (Creswell, 2014; Locke, Spirduso, & Silverman, 2014). These goals informed the research questions for study and guided the development of a new conceptual framework of technology leadership for social justice. More specifically, I have an intellectual goal of challenging the notion that how teachers and leaders approach technology is a monolithic or dichotomous concept that can only be measured on a continuum from good to poor usage or can be reduced to a set of generic behaviors. Kruger-Ross (2013) notes, “The inclusion of technology in education needs to be examined not as purely instrumental, neutral, or natural but rather as a part of the framework for a way of life in schools” (p. 302). In supporting change in modern-day schools,
leaders must understand that the school cultures they establish in relation to their leadership with technology promotes norms for how teachers and students use digital tools in the classroom. As such, I offer that technology leadership for social justice as a new conceptual framework could answer this call for a more theoretical understanding of the individual and organizational processes that influence how teachers and leaders use technology in order to “provide a much greater ability for meaningful education and empowerment of all involved in the educative process” (Kruger-Ross, 2013, p. 305).

Second, my dissertation has the practical goal to create an integrated conceptual and empirical framework of technology leadership for social justice to aid in evidence-based and equity-focused school leadership with educational technology. In describing the future of educational leadership research, Riehl (2016) offers that there is “an overemphasis on the technical-rational aspects of leadership at the expense of more critical, value-centered approaches to education” (p. 226). Although there is a vast body of research that explicates core technical aspects of educational leadership, instructional technology, and culturally responsive education separately, I argue that the complex, sociocultural challenges of leadership in today’s schools compel the need for new research that brings these three areas together conceptually and methodologically through a critical lens. Thus, to accomplish this practical goal, my research employs a systematic review of literature that synthesizes the extant literature in leadership, educational technology, and culturally responsive education to inform a more socially-conscious framework for future technology leadership research. In addition, I offer that typology research that explores teaching, leadership, and technology use with generalizable data at the national and state levels is a new approach to help school and district leaders with their evidence-based
decision making and improvement in implementing educational technology initiatives within their own school and district contexts.

Third, this study will fulfill a personal goal for me as my identity as an educator, researcher, school leader, and educational technologist is intertwined with the call to leverage the transformative potential of technology for instructional and leadership innovation. Technology is truly changing the worlds of students, teachers, and educational leaders (Collins & Halverson, 2018). Nonetheless, as an educator and school leader of color who is acutely aware of the marginalization, discrimination, and segregation that many students from historically underserved schools face, I realize that educators and researchers must always approach sweeping, glossy educational policy solutions with a heightened sense of skepticism. As a result, I truly believe that we need more critical technology leadership research that interrogates an existing literature base that largely reinforces a type of confirmation bias about the perceived impact of technology on digital age teaching and leadership. My proposed dissertation reorients this tendency to accept the digital status quo in schools by considering the question: To what extent is technology a reflection of or a panacea for our educational problems, and to what extent can a new theoretical model of technology leadership for social justice help educational leaders tinker with “preserving what is valuable and reworking what is not” (Tyack & Cuban, 1995, p. 5) when it comes to culture, teaching, technology, and leadership? My hope is that this dissertation offers school and district leaders a new paradigm for educational leadership in the digital age that disrupts the digital norm and helps them leverage the power of emerging educational technologies to validate diverse student voices in the classroom, to support adult learning for instructional improvement, to promote data-driven leadership practice, to fight systemic educational inequality, and to encourage culturally responsive praxis.
Conclusions

Technology will continue to have an omnipresent influence in today’s schools. As schools and districts continue to purchase the latest digital devices and as educators continue to learn to use them, how school and district leaders adapt their leadership and answer the call to anchor their technology leadership in equitable and impactful ways is becoming the next challenging reality for the modern-day educational leader. My dissertation pushes for the more critical conception of *technology leadership for social justice* as one mechanism that school and districts leaders can use to reflect on their own positionality in understanding the power and privilege that technology and leadership can have to reinforce problematic consequences of educational inequality, discrimination, and segregation and to anchor their technology leadership behaviors in conceptions of *technology leadership for school justice* in pursuit of meaningful and lasting educational change for all students and teachers.

The main body of this dissertation consists of three chapters, all with their own abstract, reference lists, and set of appendices. Each chapter of the dissertation is a research article that could stand alone as an independent manuscript or publication.
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Chapter II – ARTICLE ONE

“Toward a Typology of Technology-Using Teachers: A Three-Step Latent Class Analysis (LCA) of the NCES Teachers’ Use of Educational Technology in U.S. Public Schools, 2009 (FRSS 95)”

Abstract

Purpose: School leaders have heavily invested in the promise that technology could catalyze systemic school change, despite inconclusive evidence of its impact on student achievement across different school settings. Prior research has focused on understanding how and why teachers use technology in order to address this concern. However, the present study argues that an understudied third perspective – examining what types of technology-using teachers exist – could provide new insights for school leaders. Method: Using three-step latent class analysis (LCA) with nationally generalizable data from the Teachers’ Use of Educational Technology in U.S. Public Schools, 2009 Fast Response Survey System (FRSS 95), collected by the National Center for Education Statistics (NCES), I investigate the extent to which there are different types of technology-using teachers, as well as the extent to which teacher and school-level variables predict membership in these different subgroups. Findings: I find that there are four statistically significant subgroups of technology-using teachers: Dexterous (24.4%), Evaders (22.2%), Assessors (28.4%), and Presenters (24.8%). I also find that socioeconomic status, school type, enrollment, years of teaching experience, and number of computers predicted membership in the four subgroups. Implications: As one of the first nationally generalizable snapshots of teacher technology use in schools, this study provides strong evidence that technology-using teachers are not a monolithic group that is randomly distributed across schools. I discuss implications for a new framework of technology leadership for social justice that tackles inequities in teachers’ knowledge and use of technology and that challenges the belief that technology is values neutral.
Introduction

The purpose of this study is to examine the extent to which there is a typology of technology-using teachers using a nationally generalizable dataset, the Fast Response Survey System Teachers’ Use of Educational Technology in U.S. Public Schools, 2009 (FRSS 95) from the National Center for Education Statistics (NCES). Over the last decade, there has been a palpable enthusiasm in the transformative potential of educational technology to improve teaching and learning. Many school and district leaders have capitalized on this excitement for new digital tools based on the assumption that integrating instructional technology in the classroom could lead to richer, highly personalized, and collaborative learning experiences for all students (Collins & Halverson, 2009; U.S. Department of Education, 2016). The influx of new technology tools into classrooms has impacted the educational landscape in three key ways. First, similar to increased use of computers and Internet by the general public (Smith, 2017), recent policy reports show that teacher technology use has also increased steadily over the past five years (Bill and Melinda Gates Foundation, 2015; Purcell, Heaps, Buchanan, & Friedrich, 2013). Second, as access and use of technology in schools grows, school technology budgets continue to increase at an unprecedented rate as well, with national estimates for educational technology expenditures topping one billion dollars in 2014 (Winters & McNally, 2014) and projected market growth for educational technology reaching to $252 billion by 2020 (EdTechXGlobal, 2016). And third, as school leaders look for a return on their investment, there has been a growing and significant body of research that investigates the extent of technology integration efforts and its impact on teacher pedagogy and larger school change efforts (Becker, 2016).

1 A version of this chapter entitled “Toward a typology of technology-using teachers in the ‘new digital divide’: A latent class analysis of the NCES Fast Response Survey System Teachers’ Use of Educational Technology in U.S. Public Schools, 2009 (FRSS 95), has been edited for the peer-reviewed journal, Teachers College Record, and can be found at http://www.tcrecord.org/Content.asp?contentid=22277.
2000; Lemke, Coughlin, & Reifsneider, 2009; Lesgold, 2003; Wenglinsky, 1998), particularly in historically underserved communities (Darling-Hammond, Zielezinski, & Goldman, 2014; Warschauer, 2000). Indeed, teachers, school leaders, policy makers, and researchers hope to utilize the potential of technology as a catalyst to improve schooling for the next generation.

However, several researchers have noted that the conversation surrounding technology in schools is a red herring in school reform that has yet to produce clear and definitive results. Larry Cuban (2015a) warns, “The evidence thus far that increased access and use of these technological tools has, indeed, solved any of the problems is distressingly missing.” While some research studies find that technology has a small, positive effect on student achievement (Bowers & Berland, 2013; Gulek & Demirtas, 2005; Kulik, 2002; Lowther, Ross, & Morrison, 2003; Silvernail & Buffington, 2009; Silvernail & Gritter, 2007), others find that technology use is unrelated to positive student achievement growth (Cuban, Kirkpatrick, & Peck, 2001; Dynarski et al., 2007; OCED, 2015; Vigdor, Ladd, & Martinez, 2014). Additionally, numerous social justice dilemmas of the “new digital divide” have complicated technology adoption efforts and have created significant challenges for school leaders looking to use technology as a tool for school improvement. A significant body of research (Becker, 2007; Gorski, 2005; Harris, 2015; Warschauer, Knobel, & Stone, 2004; Warschauer & Matuchniak, 2010) asserts that teachers’ technology use, especially in historically underserved communities, is inherently moderated by an unjust system of inequitable access to digital tools and instructional resources. Although school leaders are key to removing these barriers to technology use (An & Reigeluth, 2011; Kopcha, 2012), principals struggle to address issues of digital inequity that go beyond access and usage toward a fundamental understanding of how certain technologies might create new disparities or reinforce social structures and biases that exist within their school communities and
contexts (Anderson & Dexter, 2005; Bowers, 1992; Dexter, Seashore-Louis, & Anderson, 2009; Reich, Murnane, & Willett, 2012). Because of this, although schools continue to adopt new technologies year after year, a “cyclic amnesia” (Zhao, Zhang, Lei, & Qiu, 2016, p. 2) of the relationship between teachers and technology continues to fester. Thus, as emerging research investigates and uncovers the tools and mechanisms school leaders need to support teacher technology use, examining technology-using teachers from a different lens could provide more clarity within this longstanding debate and could enhance school efforts to support instructional technology interventions.

Research on teacher technology use is extensive, and recent peer-reviewed and practitioner-focused literature describes teacher technology use from three perspectives: how teachers use technology, why teachers use technology, and which types of teachers use technology. First, a significant body of research (Becker, Wong, & Ravitz, 1998; Koehler & Mishra, 2009; McKnight et al., 2016; Mishra & Koehler, 2006; O'Dwyer, Russell, & Bebell, 2004, 2005; Rowand, 2000; Russell, Bebell, O'Dwyer, & O'Connor, 2003a) argues for a more multifaceted conception of how teachers use technology, rather than measuring it through a single construct. In the second perspective of examining why certain teachers use technology more than others, Heitink et al. (2016) add that teachers tend to adopt technology to simply engage students and to support learning goals and activities, while Hew and Brush (2007) identify another 123 external and internal moderating factors. However, in terms of the third perspective, there are very few examples in the literature that investigate which types of teachers use technology. For example, Cuban (2015b) spotlights one diagram where a teacher used a pencil as a metaphor to describe several different types of teacher technology users. In this diagram, the pencil tip was termed the technology “leaders,” while the “erasers” were out to
“undo the work of the leaders” (Cuban, 2015b). In the peer-reviewed literature, there are also two qualitative studies (Donnelly, McGarr, & O'Reilly, 2011; Mama & Hennessy, 2013) that describe at least four subgroups of technology-using teachers in schools in Cyprus and in Ireland. Nonetheless, there are no studies to date that test the veracity of these hypotheses around teacher technology types with empirical, nationally representative data from the United States.

Thus, the motivation of this study is to extend the research on teacher technology use and to investigate the extent to which there is a typology of teachers who use technology in their classrooms using a nationally generalizable dataset, the NCES Fast Response Survey System Teachers’ Use of Educational Technology in U.S. Public Schools, 2009. By using recent innovations in person-centered statistics and typology subgroup analysis, namely latent class analysis (LCA), I find that there are four significantly different subgroups of technology-using teachers: Dexterous (24.4%), Evaders (22.2%), Assessors (28.4%), and Presenters (24.8%). I also find several demographic variables, such as student socioeconomic status, school type, enrollment, years of teaching experience, and total number of computers, significantly predict the odds of a teacher belonging to the Evaders, Assessors, and Presenters groups.

I argue that the implications of a nationally generalizable typology of teacher technology types could be a critical piece of the reform puzzle as school leaders design evidence-based interventions that address the needs of technology-using teachers on the ground level of implementation (Culp, Honey, & Mandinach, 2003). I also provide strong evidence that technology-using teachers are not a monolithic group that is randomly distributed across schools. The nationally generalizable findings from this study reveal a startling reality that teachers in low income communities still struggle to access the adequate resources to adopt and use new technologies in instruction in meaningful and impactful ways (Harris, 2015; Valadez & Duran,
2007; Warschauer, 2003), despite the persistent rhetoric that positions teachers’ use of educational technology as the great equalizer in schools (Gorski, 2009). In all, my goal is that this person-centered conception of teacher technology use can provide a clearer picture for school leaders as they adopt technology leadership for social justice (Chapter 4, this volume) as a framework to challenge the widely-held belief in schools that technology is values neutral (Bowers, 1988, 1992; Kruger-Ross, 2013; Webster, 2017; Zhao, Alvarez-Torres, Smith, & Tan, 2004) and to establish organizational processes that provide equitable access to the tools and knowledge needed to leverage the power of educational technology to enhance learning experiences and outcomes for both students and teachers.

**Literature Review**

Instructional technology literature contains a significant and growing body of teacher technology use research. This literature can be divided into three key perspectives: *how* teachers use technology, *why* teachers use technology, and *which types* of teachers use technology.

**How Teachers Use Technology**

It is difficult to concretely describe *how* teachers use technology because our understanding of this question has evolved over time. Early survey research in the late 1990s described that teachers were only using technology to prepare for instruction (Market Data Retrieval, 1999). However, subsequent research findings showed that teachers’ use of digital tools was much more multidimensional than once thought. These researchers criticized early surveys for confounding the indicators of teacher technology use into a single generic construct (Bebell, Russell, & O'Dwyer, 2004; Rowand, 2000). Instead of describing how teachers use technology as a single action, through several studies that use confirmatory factor analysis with large scale surveys (Russell, O'Dwyer, Bebell, & Miranda, 2004), research finds that the
construct of how teachers use technology is characterized by seven positively correlated indicators: (1) teachers’ use of technology for class preparation; (2) teachers’ professional email use; (3) teachers’ use of technology for delivering instruction; (4) teachers’ use of technology for accommodation; (5) teacher-directed student use of technology during class time; (6) teacher-directed student use of technology to create products; and, (7) teachers’ use of technology for grading (Russell et al., 2003a; Russell et al., 2004). Likewise, in their study on teachers’ use of educational technology in seven states, McKnight et al. (2016) found that teachers use technology for communication, direct instruction of content, accommodations, collaboration, research, and assessment. This multifaceted understanding of how teachers use technology over time was, and continues to be, a critical part of how researchers capture a more complex snapshot of how teachers use digital tools across different school settings and attempt to build a theory of teacher technology use (Bebell et al., 2004; Koehler & Mishra, 2009; Mishra & Koehler, 2006).

Although we understand that teachers use technology in a variety of ways, there is still a significant problem in understanding how teachers use technology within this new multidimensional construct (Bebell et al., 2004; Russell et al., 2003a). This problem persists for three main reasons. First, despite evidence that shows that teachers have varied technology use habits (Rowand, 2000; Russell et al., 2004), policy makers and school leaders continue to perpetuate a broad and superficial definition of how teachers use technology in the professional learning and evaluation of teachers, focusing on if a teacher can use digital tools rather than how he or she is using them (Bebell et al., 2004; Cuban, 2001, 2015a; Lawless & Pellegrino, 2007; Russell et al., 2003a). Second, our current measures of teacher technology use do not factor a wide array of individual and contextual factors that may influence how a teacher integrates
technology in instruction (Lesgold, 2003; Wenglinsky, 2005). Third, issues of equity and access have complicated how we understand how teachers use technology in diverse school environments. Warschauer (2000) notes:

In analyzing [the] integration of technology into instruction, Cuban (1993) proclaimed that “computers meets classroom: Classroom wins” (p. 185) [...] the computer “beats” the classroom, it doesn’t necessarily beat the system. [Technology in schools] can all leave intact or even reinforce patterns by which schools channel students into different social systems. (p. 18)

In other words, as technology enters learning spaces in diverse contexts, social justice dilemmas pertaining to access, use, and skill unduly influence how certain teachers in certain contexts envision technology integration (An & Reigeluth, 2011; Kopcha, 2012; Valadez & Duran, 2007). Consequently, new research emerged to investigate the individual and school-level barriers on why certain teachers use technology in order to address these prevailing challenges.

**Why Teachers Use Technology**

Ertmer (1999) describes two types of barriers that influence why certain teachers use technology more than others, referred to as *first-order* barriers and *second-order* barriers. First-order barriers are defined as “obstacles that are extrinsic to teachers [such as] the types of resources (e.g., equipment, time, training, support) that are either missing or inadequately provided in teachers’ implementation environments” (Ertmer, 1999, p. 50). When first-order barriers exist, there are fewer opportunities for teachers to integrate technology in instruction (Cuban et al., 2001; Ertmer, 1999; Hew & Brush, 2007; Mumtaz, 2000). While policy talk tend to focus on first-order barriers, second-order barriers present a more difficult challenge, where action is “rooted in teachers’ underlying beliefs about teaching and learning and may not be immediately apparent to others or even to the teachers themselves” (Ertmer, 1999, p. 51). A significant body of research (Cho & Littenberg-Tobias, 2016; Ertmer, 2005; Ertmer &
Ottenbreit-Leftwich, 2010; Ertmer et al., 2012; Hsu, 2016; Levin & Wadmany, 2006; Palak & Walls, 2009) has found that teacher beliefs, attitudes, and enacted values with technology and instruction are closely associated with why certain teachers choose to integrate technology in their classroom practice. Although research has outlined many of the barriers, there are still lingering questions about how this knowledge translates into practice.

There is still no clear picture of the relationship between first- and second-order barriers and how this relationship influences different types of teachers who use technology (Ertmer, 1999; Hew & Brush, 2007). Ertmer (1999) asks two critical questions about these barriers and their relationship with teachers:

Do teachers at higher levels of use encounter relatively fewer first- and second-order barriers? In what ways are barriers that are encountered by teachers at higher levels of technology use similar or dissimilar to those encountered by teachers at lower levels of use? (p. 52)

Ertmer (1999) opens up the possibility that teachers with similar technology usage patterns could have different experiences with certain second- and first-order barriers. Likewise, as these barriers exist within the sociocultural context of a school (Sherman & Howard, 2012; Windschitl & Sahl, 2002), comparing these subgroups of technology-using teachers could provide additional insight into how action, intent, and context are interrelated when teachers use technology in their classrooms. As such, another perspective emerges to further explain teacher technology use – whether or not different types of technology-using teachers exist.

**What Types of Teachers Use Technology**

The third perspective, which types of teachers use technology, is a growing subset of research in the area of teacher technology use. The Rogers (1962) innovation adopter categories were arguably the first technology user typology to describe user technology habits. Rogers (1962) theorizes that users who adopt technology can be divided into five user segments:
innovators, early adopters, early majority, late majority, and laggards. While the first three are characterized by quick adoption of new tools, the last two are more reluctant to learn new technologies and integrate them in their practice (Rogers, 1962). The Rogers (1962) adopter categories spawned several other typologies of technology-using teachers in the literature.

There are two small-scale qualitative studies that classify different types of teachers who use technology. Table 2-1 outlines the typologies in both of the studies. After interviewing thirteen (n=13) Irish science educators about their use of a computer program, Donnelly et al. (2011) theorize four subgroups of teachers who integrate technology into their instructional practices: contented traditionalist, the selective adopter, the inadvertent user, and the creative adapter. While creative adapters and selective adopters are intrinsically empowered and motivated to integrate technology into their pedagogical practice and open to new types of teaching tools and methods, the contented traditionalist and inadvertent user tend to adopt technology only by force or pressure from their colleagues.

Likewise, Mama and Hennessy (2013) also conduct a multi-case study on the technology use habits and beliefs of eleven (n=11) teachers in Cyprus and argue for four distinct subgroups of teachers. For example, Group A, the high user group, consists of teachers who are both integrational and diversifying, meaning their use of technology align with lesson objectives and their beliefs center on technology as a tool for differentiation. In contrast, Group D, the low users, describes a teacher who is more inimical and subversive (Mama & Hennessy, 2013).
<table>
<thead>
<tr>
<th>Author and Year, Literature Type</th>
<th>Sample Size</th>
<th>Research Analytical Method</th>
<th>Summary of Findings</th>
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| Donnelly et al. (2011) Peer-reviewed article | 13 (N = 13) science teachers and other education stakeholders | Qualitative; semi-structured interviews | Four (4) subgroups:  
  - *Contented traditionalist*: focus on assessment, fatalistic, low technological pedagogical content knowledge  
  - *Selective adopter*: focus on assessment, teacher-centered but willing to change, high technological pedagogical content knowledge but only when preparing for assessment  
  - *Inadvertent user*: use from external pressure, student-centered but unaware of classroom implications, lack of ownership, low technological pedagogical content knowledge  
  - *Creative adapter*: strong student-centered approach, adaptable pedagogy, strong sense of purpose and empowerment, high and varied technological pedagogical content knowledge |
| Mama and Hennessy (2013) Peer-reviewed article | 11 teachers (N = 11) in elementary school | Qualitative; multi-case study | Four (4) subgroups:  
  - *Group A* (n = 2): Moderate to high usage, constructivist-oriented purpose, encourages autonomous learning, use related to lesson objectives  
  - *Group B* (n = 3): Low to moderate usage, engagement-oriented purpose, encourages student motivation, use related to student technical knowledge  
  - *Group C* (n = 5): High usage, administrative-oriented purpose, encourages research skills and information gathering, use related to improving teacher efficiency  
  - *Group D* (n = 1): Moderate to low usage, necessity-oriented purpose, distracts students, lack of use related to fear and threat to authority |
Collectively, this research on typologies of technology-using teachers (Donnelly et al., 2011; Mama & Hennessy, 2013) highlights three common themes. First, these studies highlight the need for more person-centered approaches in describing technology-using teachers. Arguably, the qualitative findings from these studies provide the first robust, person-centered descriptions of the technology-using teacher. Second, in all three typologies, frequency of use (low, middle, and high use) appears to be an organizing characteristic in designating subgroups of technology-using teachers. Third, the findings from both of these studies describe at least four, mutually exclusive subgroups of technology-using teacher types.

Although these studies provide some of the first descriptions of which types of teachers use technology, there are still prevailing concerns pertaining to the validity, the generalizability, and sociocultural implications of the findings. As mentioned earlier, there is a clear consensus in the literature that teacher technology use should be measured in a more multidimensional fashion (Bebell et al., 2004). However, each of the two aforementioned studies only investigate teacher technology users from the perspective of one of the seven significant correlates of teacher technology use (Bebell et al., 2004). In addition, although large-scale data on teacher technology use is scarce, the small sample size, the absence of statistically significant groupings, and the lack of actual membership proportions per subgroup raise additional questions about the generalizability of the findings to all technology-using teachers. Finally, research suggests that there is a “digital divide” between high- and low-income schools in access to digital tools, content, and teacher resources for technology-focused curriculum and instruction (Gorski, 2005; Natriello, 2001; Valadez & Duran, 2007; Vigdor et al., 2014; Warschauer, 2016; Warschauer et al., 2004; Wenglinsky, 1998). Mama and Hennessy (2013) and Donnelly et al. (2011) fail to describe differences in access because the researchers examine teacher technology use within
one school setting. Understanding how teacher types may differ across school settings should be the next frontier for teacher technology user typology studies. Thus, the motivation of my study is to address these issues described above by using latent class analysis (LCA), a mixture modeling approach that statistically tests the extent to which there are subgroups of similar individuals within a nationally representative dataset of teachers across U.S. schools.

**Framework of the Study**

Identifying subgroups of teachers in schools with national data has become an emerging trend in educational research. Typology subgroup studies typically use methods such as cluster analysis to develop profiles of students and teachers (Antonenko, Toy, & Niederhauser, 2012). Although cluster analysis produces meaningful groupings, the method does not embed a hypothesis test in the analysis, leaving measures of best fit up to the interpretation of the researcher (Vermunt & Magidson, 2002). This study utilizes latent class analysis (LCA) to statistically determine the extent to which there are homogenous groups of individuals within a heterogeneous dataset (Asparouhov & Muthén, 2008; Henry & Muthén, 2010; Jung & Wickrama, 2008).

There is a wealth of other education research that uses latent class analysis to explore typologies of different teachers, leaders, and schools. For example, Boyce and Bowers (2016) identified two significantly different types of principals who exit their schools. The first group, *Satisfied* principals, reported higher satisfaction with their job performance, salary, attitude, and self-perception of their leadership than the second group, the *Disaffected*. In another example, Brasseur-Hock et al. (2011) found that there are four significantly different levels of students and their reading comprehension levels. Finally, in validating the Comprehensive Assessment of Leadership for Learning (CALL) survey in a two-level LCA, Bowers et al. (2017) argued for
three significantly different groups of teachers in three types of schools that enact leadership for learning behaviors, using the ordinal grouping of low, moderate, and high leadership for learning teachers and schools.

Yet, despite interest in this type of analysis in education research and the wealth of literature on teacher technology use in schools, little is known about the extent to which there are different groups of teachers who share similar technology usage habits. While the majority of research in the domain of educational technology focuses on how and why teachers use technology to describe and to generalize teacher technology integration efforts, the goal of this study is to explore if there are underlying subgroups of similar teacher technology users within nationally generalizable data, while also exploring various teacher-level covariates that could predict membership in the subgroups. Thus, the research questions for this study are:

1) Using a nationally representative dataset, to what extent are there different types of teachers who use technology?

2) To what extent are other contextual factors, such as urbanicity, percentage of free / reduced lunch, total number of classroom computers, school type, years of teaching experience, and enrollment, associated with membership in these subgroups of technology-using teachers?

Methods

Data Sources

This study is a secondary analysis of the public use data from the Fast Response Survey System – Teachers’ Use of Educational Technology in U.S. Public Schools, 2009 (FRSS95). This survey was originally collected in 2009 by the National Center for Education Statistics and had a representative sample size of 3,159 teachers from public schools across the United States.
Weights were provided through a complex probabilistic weighting strategy so that findings can be generalizable to all 2.39 million public school teachers in the US in 2009 (National Center for Education Statistics, 2009). The data on teachers’ use of educational technology includes information on the use of computers and Internet access, teacher responses on students’ use of educational technology, teacher professional development, and availability of technology resources (Gray, Thomas, Lewis, & Tice, 2010).

The FRSS 95 provides a unique opportunity to explore teacher technology types with national data. As such, I selected this data for five reasons. First, although the dataset contains variables directly related to educational technology, research that uses the FRSS 95 dataset to describe teachers’ use of educational technology is virtually nonexistent. Second, it directly relates to factors that influence teacher technology use in schools (Gray et al., 2010), a clear application to the research questions at hand. Third, with the statistical weights applied, FRSS 95 is nationally generalizable (National Center for Education Statistics, 2009), and findings from this study could contribute to current research, practice, and policy in field of educational technology. Fourth, the FRSS 95 is the most recent, nationwide data available on teacher technology surveying teachers in 2009, at the time of analysis. And fifth, as Coffland and Strickland (2004) found a direct relationship between teacher disposition to use technology and the principal attitudes toward technology integration, it is critical to gain a more empirical understanding of how teachers use technology first before moving on to the overall goal of this dissertation to understand teacher perceptions of technology use and technology leadership.

The sample for this study relies on a subset of the full FRSS 95 dataset. Given the related literature and research questions for the study, I selected teachers based on their frequency of technology use. Teachers who responded “rarely,” “sometimes,” or “often” (i.e., some degree of
technology usage) for question (Q2A), “how frequently do you or your students use computers during instructional time in your classroom,” were used in the final analysis. All other responses (“never” or “not applicable”) were excluded. Of 3,159 teachers in the full sample, I examined a subset of \( n = 2,764 \) teachers who indicated that they use technology in their classrooms.

I also applied the final sampling weights (TFWT) from FRSS 95 to the data so that the results of the LCA could be generalized to a national population of technology-using teachers in the United States in 2009.

**Variables Included in the Analysis**

The indicators and covariates included in the analysis are based on the literature and theory on teacher technology use. The indicator variables focused on the measures of the teacher technology use construct as outlined in the Bebell et al. (2004) study. The covariates were selected based on teacher and school factors that previous literature identified as being associated with teacher technology use.

**Teacher use of technology for instruction.** The 2009 FRSS 95 included fifteen questions related to how teachers use technology in their preparation for direct instruction. I did not include all fifteen questions in the study, omitting questions that asked about specialized software (e.g., photo editing software), word processing programs and Internet browsers, or resources that are typically censored in public schools (e.g. social media). I omitted these questions based on prior research that suggests that certain technologies have been institutionalized by teachers as they prepare for instruction and do not add a significant contribution to understanding how teachers use technology in schools (Adams, 2006; Kuiper & de Pater-Sneep, 2014; Russell, Goldburg, & O'Conner, 2003b). Furthermore, maintaining a parsimonious model closely related to the relevant literature is helpful to maintaining the
appropriate level of statistical power (Boyce & Bowers, 2016; Dziak, Lanza, & Tan, 2014). I included the following variables in this measure: making presentations, administering computer-based tests, and using drill, practice, and tutorial software programs. Teachers were asked to rate their frequency of use on a four-point scale. For this study, responses will be dichotomized into high to moderate (1 = “often / sometimes”) and low to none (0 = “rarely / never”) usage of technology for direct instruction. Specifics on the survey questions used, response coding schema, and the descriptive statistics for these and other variables can be found in Appendix B.

**Preparation to use technology.** The 2009 FRSS 95 included six questions that asked teachers about their preparation to use educational technology in their school, three of which were used for this study. I included activities, such as professional learning activities (Brinkerhoff, 2006), training from technology staff (Ausband, 2006), and independent learning (Yan & Piper, 2003), in the model based on relevant literature. Using a four-point scale, teachers were asked about the extent to which these activities have prepared them to use technology. Responses will be dichotomized into not at all (0 = “not at all”) and to some extent (1 = “minor / moderate / major extent”).

**Disposition toward professional learning.** The 2009 FRSS 95 included one question that asked teachers if their professional learning in technology met their needs and goals. I included this variable in response to the Vannatta and Fordham (2004) findings that a teacher’s willingness to change and their effort to participate in professional learning predicts classroom technology use. Measured on a four-point scale, questions measured how teachers responded negatively or positively toward whether technology professional development met their goals. Responses will be dichotomized into either positive (1 = “somewhat agree / strongly agree”) or negative (0 = “somewhat disagree to strongly disagree”).
**Use of technology for productivity.** The 2009 FRSS 95 included twelve questions that asked teachers how often they use technology for certain productivity tasks. I included questions about email to students and parents, as well as student record management, based on Bebell et al. (2004) study that listed these two specific scales (i.e., email and grading) to be associated with the teacher technology use construct. Teachers were asked to rate their frequency of usage on a four-point scale. For the analysis, responses will be dichotomized into high to moderate (1 = “often / sometimes”) and low to none (0 = “rarely / never”).

**Teacher-directed student use of technology for discrete and hands-on skills.** The 2009 FRSS 95 included thirteen questions that asked teacher-directed student use of technology, seven of which were used in the analysis. Many questions were omitted because the majority of the respondents answered “not applicable” to the question. The questions for this indicator have been divided into technology to learn discrete skills and to perform hands-on tasks based on extensive research on how certain classroom activities benefit from the integration of technology and lead to increased student transfer and understanding of content (Bransford, Brown, & Cocking, 2000). Activities involving discrete skills include preparing written text, learning and practicing basic skills, conducting research, and solving problems with data and calculations. Teacher-directed student uses of technology for hands-on skills include developing multimedia (Neo & Neo, 2009), making art and other creative mediums (e.g., music, movies, and webcasts) (Greenhow, Robelia, & Hughes, 2009), and conducting experiments (Newman et al., 2012). Similar to using technology for productivity, responses will be dichotomized into high to moderate (1 = “often / sometimes”) and low to none (0 = “rarely / never”).

Across the variables, missingness ranged from 0% to 25%. Following the recommendations for missing data in samples of this type of analysis (Strayhorn, 2009), I will
rely on missing data imputation using Full Information Maximum Likelihood (FIML) as recommended in the LCA modeling literature (Asparouhov & Muthén, 2013; Enders, 2010; Vermunt & Magidson, 2007).

**Covariates.** Hew and Brush (2007) have identified 123 extrinsic and intrinsic teacher and school related factors that influence how teachers integrate technology into the classroom. Due to the rapid data collection strategy employed by the Fast Response Survey System program (National Center for Education Statistics, 2009), most of these factors are not included in the survey questionnaire. Still, I have included some teacher-level demographic factors, such as years of teaching experience, as well as school-level demographics factors, such as urbanicity, percentage of students on free and reduced lunch, school type, enrollment, and number of total computers, in the model. There were no missing data from the covariates. Descriptive statistics, variable recodes, and survey question used for the covariates can be found in Appendix 2-A.

**Analytic Model**

I used a three-step latent class analysis (LCA) framework for this study to determine if there were significantly different types of teachers who use technology in schools. Equation 2-1 are the statistical equations for the LCA (Collins & Lanza, 2010). In general, LCA is a subset of mixture modeling which is useful in determining the extent to which there is one or more than one subgroup of responders within a dataset (Jung & Wickrama, 2008; Masyn, 2013; Múthen, 2002, 2004; Muthén & Asparouhov, 2002; Samuelsen & Raczynski, 2013; Vermunt & Magidson, 2004). I selected LCA as the analytic technique because LCA evaluates how groups of individuals differ or relate to one another, or simply put, the method is person-centric (Boyce & Bowers, 2016; Jung & Wickrama, 2008). In contrast to previous studies on teachers’ technology use that focus on how different technology use indicators relate to one another
(Bebell et al., 2004; Ertmer, Ottenbreit-Leftwich, & York, 2006), the research questions here are centered on the teachers, and as such, LCA was the most suitable analytic model.


\[ P(Y = y| x_i, g) = \sum_{c=1}^{C} \gamma_{c|g}(x_i) \prod_{m=1}^{M} \prod_{k=1}^{r_m} \rho_{mk|cg}^{I(y_{im}=k)} \quad (1) \]

\[ \gamma_{c|g}(x_i) = P(C_i = c|x_i,G_i = g) = \frac{\exp(\beta_{0c|g} + x_i\beta_{1c|g})}{1 + \sum_{j=1}^{C-1} \exp(\beta_{0j|g} + x_i\beta_{1j|g})} \quad (2) \]

In which:
- \( c \) = classes in latent class model
- \( m \) = categorical items
- \( x \) = covariate for individual \( i \)
- \( g \) = value of individual \( i \) group membership
- \( j \) = value of individual \( i \) group membership
- \( i \) = individual responses to \( m \) items
- \( \gamma \) = latent class membership probabilities
- \( \rho \) = item response probabilities conditional on latent class membership
- \( \beta \) = logistic regression coefficients for covariates
- \( Y_i \) = vector of individual \( i \) responses to \( m \) survey

As standard in these types of analyses, Figure 2-1 is the structural and conceptual equation model that I tested for the study. The large circle in the middle of the structural equation model, labeled as “Latent Classes C,” the different subgroups of technology-using teachers are determined based on the seven indicator variables described above: use of technology for instruction, preparation to use technology, disposition toward professional learning, use of technology for productivity, teacher-directed use of technology for productivity, and teacher-directed student use of technology for hands-on tasks. I then added six covariates (identified on the left side of figure as urbanicity, percentage of free / reduced lunch, total number of classroom computers, school type, years of teaching experience, and enrollment) as control variables.
Structural and Conceptual Equation Model of 3-Step Latent Class Analysis (LCA) of NCES FRSS 95. The subgroups of technology-using teachers are estimated in relation to teacher responses to their use of technology in instruction, preparation to use technology, disposition toward professional learning, use of technology for productivity, and teacher-directed student use of technology for discrete and hands-on tasks. Covariates predict subgroups of technology-using teachers. Distal outcomes were not included in the model due to absence of available teacher outcome data.
All statistical procedures will be performed in *MPlus, version 7.4* (Muthén & Muthén, 2012). The *MPlus* code used for the analysis is included in Appendix 2-B. Following the latent class analysis literature, this study used a three-step LCA structural equation modeling framework (Asparouhov & Muthén, 2013; Kim et al., 2016; Lanza, Tan, & Bray, 2013; Vermunt, 2010). First, as suggested in the literature (Jung & Wickrama, 2008; Nylund, Asparouhov, & Muthén, 2007; Nylund-Gibson, Grimm, Quirk, & Furlong, 2014), I performed an initial LCA using the indicator variables to determine the number of statistically different types of technology-using teachers through hypothesis testing. This initial step only includes the indicator variables to ensure that no other variable would confound how the groups are identified. Each respondent is then assigned to the most likely class.

In this step, LCA uses an iterative process with a different number of classes in each model in order to determine model fit. However, there is no one method in the literature that is considered the best way to correctly indicate the proper number of classes in the model (Bakk & Vermunt, 2016; Dziak et al., 2014; Jung & Wickrama, 2008; Lo, Mendell, & Rubin, 2001; Muthén & Asparouhov, 2002; Tofighi & Enders, 2008; Vermunt & Magidson, 2004). There are two conventions described in the literature. In the first method, some research suggests using the Bayesian information criteria, a statistic that compares the BIC of the current model, $k$, with the BIC from the $k$-1 class model (Magidson & Vermunt, 2004; Muthén & Asparouhov, 2002; Nylund et al., 2007). In other words, when performing the analysis, a model with a specific number of classes is estimated one at a time, progressively increasing in number of classes until the specified model has a larger BIC value than the previous (Jung & Wickrama, 2008; Nylund et al., 2007). When this occurs, the previously selected model is the best fit. In contrast, the Lo-Mendell-Rubin (LMR) adjusted likelihood test can be used to determine model fit as well, using
a hypothesis test to determine whether the current model, \( k \), is a better, statistically significant model fit than the previously estimated \( k-1 \) class model (Lo, 2005; Lo et al., 2001). Again, a model would be specified with varying number of classes one at a time until the \( p \)-value of the test is not significant. When this occurs, the previously selected model is the best fit. I considered the BIC and LMR statistics, as well as an a priori number of different subgroups \( (n = 4) \) based on previous literature, when I selected the proper number of groups in the data.

Next, using the auxiliary command (R3STEP) with the six covariates (Kim et al., 2016), I performed another LCA with a post-hoc multinomial logistic regression to estimate the odds of an individual belonging to a group based on the covariates. I omitted the last step of the three-step sequence, a chi-square testing procedure to produce distal outcomes, due to a lack of appropriate follow-up data to test in the FRSS dataset.

**Results**

I now describe four different types of technology-using teachers, along with the covariates that predict membership in these groups. To find the best model fit, I performed the LCA on a two-class model, running subsequent models that increased in the total number of specified classes until both the BIC and LMR statistics indicated the best model fit (Jung & Wickrama, 2008; Masyn, 2013; Múthen, 2002). A seven-class model was the preliminary result of the initial analysis. Based on the literature on using the LMR test (Lo et al., 2001), the five-class model had the first non-significant \( p \)-value \( (p = 0.732) \), demonstrating that the previous model, four-class model, was the best model fit for the data using this statistic. The four-class LCA model fit the data well with fit statistics of AIC = 42204.407, BIC = 42625.014, \(-\text{Log likelihood} = 21031.203\), LMR \( p < 0.001 \), and entropy = 0.674.
In addition, I also considered the BIC to determine the best model fit (Jung & Wickrama, 2008; Múthen, 2002). With this analysis, the first positive change in the BIC fit statistic occurred between the six-class model (BIC = 42513.032) and the seven-class model (BIC = 42521.286), indicating that the six-class model is the best model fit according to the BIC. However, I chose the more conservative four class model as the best fit with a significant LMR as the LMR fit statistic has been identified in the literature as the more conservative of the measures, erring on the side of a more parsimonious model fit to avoid issues of model over-interpretation (Tofighi & Enders, 2008). Although up to six classes could fit the data, I argued for and interpreted the four-class model. Table 2-2 presents the estimated model fit statistics for the each of the iterations of the seven-class model.

Table 2-2. Results and Fit Statistics for LCA of Technology-Using Teachers

<table>
<thead>
<tr>
<th>Model</th>
<th>AIC</th>
<th>BIC</th>
<th>-Log Likelihood</th>
<th>LMR Test for k-l classes</th>
<th>p</th>
<th>Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two classes</td>
<td>43232.732</td>
<td>43442.087</td>
<td>21582.366</td>
<td>3177.214</td>
<td>&lt;0.001</td>
<td>0.729</td>
</tr>
<tr>
<td>Three classes</td>
<td>42676.497</td>
<td>42990.492</td>
<td>21285.249</td>
<td>590.098</td>
<td>0.003</td>
<td>0.707</td>
</tr>
<tr>
<td><strong>Four classes</strong></td>
<td><strong>42204.407</strong></td>
<td><strong>42625.041</strong></td>
<td><strong>21031.203</strong></td>
<td><strong>504.553</strong></td>
<td>&lt;0.001</td>
<td><strong>0.674</strong></td>
</tr>
<tr>
<td>Five classes</td>
<td>42006.373</td>
<td>42533.648</td>
<td>20914.187</td>
<td>232.404</td>
<td>0.732</td>
<td>0.681</td>
</tr>
<tr>
<td>Six classes</td>
<td>41879.118</td>
<td>42513.032</td>
<td>20832.559</td>
<td>162.119</td>
<td>0.798</td>
<td>0.699</td>
</tr>
<tr>
<td>Seven classes</td>
<td>41780.732</td>
<td>42521.286</td>
<td>20765.366</td>
<td>133.450</td>
<td>0.763</td>
<td>0.710</td>
</tr>
</tbody>
</table>

*Note: AIC = Akaike information criteria; BIC = Bayesian information criteria; LMR = Lo-Mendell-Rubin adjusted likelihood ratio test*

Note: n = 2,764

Additionally, Table 2-3 shows the classification probabilities for latent class membership. The classification probabilities figure shows the probability of an individual belonging to a particular group to be placed in that group when fitting the model. In examining the probabilities in the diagonal, as well as in the off-diagonal cells, the probabilities show that the model fit the data well for the four-class model.
Table 2-3. Classification Probabilities for the Most Likely Latent Class Membership (Column) by Latent Class (Row)

<table>
<thead>
<tr>
<th>Latent Class</th>
<th>Most Likely Latent Class Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Class 1 (Evaders)</td>
</tr>
<tr>
<td>Class 1</td>
<td>0.831</td>
</tr>
<tr>
<td>Class 2</td>
<td>0.001</td>
</tr>
<tr>
<td>Class 3</td>
<td>0.088</td>
</tr>
<tr>
<td>Class 4</td>
<td>0.050</td>
</tr>
</tbody>
</table>

I identified four significantly different groups of teachers who use technology in their classrooms. I named these four subgroups Dexterous, Presenters, Assessors, and Evaders.

The LCA model identified two groups in the typical high use – low use hierarchy. The high users, or Dexterous teachers, made up approximately 24.4% of the sampled teachers. This group had a high proportion of flexible teachers who indicated using technology in a variety of functions, including for themselves to prepare for classroom activities and for directing students to use technology with hands-on and discrete tasks, such as preparing written texts, conducting research, developing multimedia presentations, and conducting experiments. Dexterous teachers also had the highest satisfaction with technology professional learning with 92.1% of these teachers indicating that the professional learning experiences with technology met their goals.

In contrast, 22.2% of teachers were in the Evaders group. This group of teachers indicated that they neither directed students to use technology to complete discrete tasks or hands-on tasks, nor did they use technology to administer tests (17.9%) or use skill and practice software (19.5%) with students. In fact, Evaders also indicated the lowest technology use for productivity, like student record management (64.5%), email with parents (41.8%), and email with students (8.4%). Although teachers in all four groups had high levels of engagement in learning about technology through professional development, 69.2% of Evaders, the lowest proportion of the four groups, reported that these experiences met their professional goals.
Interestingly, the LCA model also identified the two highest proportions of teachers in groups that use technology for specific pedagogies and teaching styles. Approximately 24.8% of the sample, the majority of teachers in the *Presenters* group reported using technology for their own classroom presentations (82.6%) and for instructing their students to use technology for their presentations (70.5%). In looking at student use with this subgroup, the *Presenters* group also has the second highest proportion of teachers (second to the *Dexterous* group) to have students use technology to prepare written texts (92.0% for *Dexterous*, 82.0% for *Presenters*) and to conduct research (95.0% for *Dexterous* and 89.4% for *Presenters*). Yet, in the second lowest proportion after the *Evaders* group, *Presenters* also indicated that they rarely use technology to prepare drill and practice instruction for students (27.4%), to lead students in solving problems and analyzing data (26.5%), to create visual or digital media (36.3%), or to conduct experiments (14.4%).

The largest proportion of technology-using teachers is the *Assessors*, who make up 28.4% of the sample. Individuals in this group indicated that they direct their students to use technology when practicing basic skills (94.0%) and when preparing for instruction with drill and practice software (77.3%). Again, the *Assessors* group shared the inclination to use technology to practice basic skills like the *Dexterous* group; however, with the second lowest usage pattern from the *Evaders*, *Assessors* indicated that they infrequently use technology to have their students create presentations (8.6%), use creative media (9.9%), and less than half of respondents have students produce written texts (47.8%). For purposes of comparison, Figure 2-2 details an indicator plot for the proportions of the indicator variables per subgroup.
Statistical indicator plot of Latent Class Analysis results showing four subgroups of technology-using teachers. The *Dexterous* teachers (24.4%) are the highest and most flexible users of classroom technology, while the *Evaders* (22.2%) have the lowest usage across the indicators. The *Assessors* (28.4%) and *Presenters* (24.8%) are the two largest groups and use technology for specific pedagogical techniques.
I now present the covariates that were examined to estimate the odds of a teacher belonging to a particular group. *Dexterous* teachers were used as the reference category to assist with interpretation, and relative effect sizes are reported based on significant differences. Results show that when a school has more than 50 percent of students eligible for free and reduced lunch, teachers are 1.36 times more likely to be in the *Assessor* group than the *Dexterous* group \((p = 0.056)\) and more than two times less likely to be a *Presenter* than *Dexterous* \((p < 0.001)\). In comparing small (less than 300 students) to medium (300 – 999 students) schools, teachers in small schools are 1.48 times more likely to be an *Evader* than a *Dexterous* technology-using teacher \((p = 0.086)\). Likewise, compared to secondary teachers, teachers in elementary schools are 1.65 times more likely to be in the Evaders group than the *Dexterous* group \((p = 0.006)\) and more than three times more likely to be an *Assessor* than *Dexterous* \((p < 0.001)\). Elementary school teachers are also 2.22 times less likely to be a *Presenter* than a *Dexterous* teacher who uses technology \((p < 0.001)\). Years of teaching experience also predicted the odds of teachers belonging to a technology user group, indicating that for every one unit increase in teaching experience, technology-using teachers are 1.02 times less likely to be an *Evader* than *Dexterous* \((p = 0.027)\) and 1.28 less likely to be a *Presenter* than *Dexterous* \((p = 0.002)\). Finally, in looking at first-order barriers for technology (Ertmer, 1999), for every one unit increase in total number of computers in a classroom, teachers are 1.29 times less likely to be in the Evaders subgroup \((p < 0.001)\), 1.07 times less likely to be in the *Assessors* subgroup \((p < 0.001)\), and 1.05 times less likely to be in the *Presenters* subgroup than be *Dexterous* \((p < 0.001)\). A summary of the means and odds of each subgroups is located in Table 2-4.
Table 2-4. Means and Odds Ratio Table for Latent Class Analysis (LCA) Covariates in NCES FRSS 95

<table>
<thead>
<tr>
<th>Variable</th>
<th>Dexterous (24.4%)</th>
<th>Evaders (22.2%)</th>
<th>Assessors (28.4%)</th>
<th>Presenters (24.8%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Odds Ratio</td>
<td>Mean</td>
<td>Odds Ratio</td>
</tr>
<tr>
<td>School urbanicity:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>City</td>
<td>0.20</td>
<td>—</td>
<td>0.23</td>
<td>0.467</td>
</tr>
<tr>
<td>Town</td>
<td>0.15</td>
<td>—</td>
<td>0.13</td>
<td>0.609</td>
</tr>
<tr>
<td>Rural</td>
<td>0.31</td>
<td>—</td>
<td>0.30</td>
<td>0.970</td>
</tr>
<tr>
<td>&gt;50% free / reduced lunch</td>
<td>0.45</td>
<td>—</td>
<td>0.47</td>
<td>0.610</td>
</tr>
<tr>
<td>School type:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elementary</td>
<td>0.54</td>
<td>—</td>
<td>0.65</td>
<td>1.65**</td>
</tr>
<tr>
<td>Enrollment:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small (&lt;300)</td>
<td>0.11</td>
<td>—</td>
<td>0.15</td>
<td>1.48~</td>
</tr>
<tr>
<td>Large (&gt;1000)</td>
<td>0.29</td>
<td>—</td>
<td>0.23</td>
<td>0.952</td>
</tr>
<tr>
<td>Years of teaching experience</td>
<td>14.36</td>
<td>—</td>
<td>13.18</td>
<td>0.98*</td>
</tr>
<tr>
<td>Number of total computers</td>
<td>6.52</td>
<td>—</td>
<td>2.81</td>
<td>0.77*** &lt;0.001</td>
</tr>
</tbody>
</table>

*Note: ~p < .10; *p ≤ .05; **p ≤ .01; ***p ≤ .001*
Discussion

This study informs the literature on teacher technology use by using a nationally
generalizable dataset to examine technology-using teachers within the current multidimensional
measures of teacher technology use. Using latent class analysis (LCA) to explore six domains of
teacher technology use variables, I identified four significantly different groups of technology-
using teachers: $Dexterous$, $Presenters$, $Assessors$, and $Evaders$. I derived the names for the four-
subgroup typology of technology-using teachers based on my narrative interpretation of the
survey response data. My hope is that the labels provide a clear and concise portrayal of how
teachers describe their technology usage habits in schools in 2009. Here, I briefly describe the
typology again with a few concrete example characteristics of the subgroups.

$Dexterous$ teachers are flexible and wide ranging users that integrate technology for
different modes and purposes. Affectionately known as the innovators and the early adopters in
the Rogers (1962) study, $Dexterous$ teachers report that they are comfortable with any type of
technology and ready to learn more through professional development opportunities. In sharp
contrast, $Evaders$ are resistant to use technology in every way, including sending emails to
students and taking daily attendance. $Presenters$ are teachers who prefer using technology to aid
with lectures and interactive whiteboard activities, while guiding students to use presentation to
produce written texts and presentations. Finally, $Assessors$ are most comfortable with using
technology with drill and practice software, directing students to use this technology to practice
basic skills in mathematics or literacy.

The findings from the study add to the teacher technology use literature in three ways.
First, this study is one of the first to use national data to examine the assumption that there are
different types of technology-using teachers. Second, my findings break out of the traditional
ordinal scale of low, medium, and high frequency of technology use as presented in past research findings (Donnelly et al., 2011; Mama & Hennessy, 2013). The results describe the differences between these teachers in their pedagogical uses of technology, their beliefs and dispositions toward technology, their personal use of technology for productivity, and how they direct students to use technology in various tasks, the first time this has been done within the same statistical model. Third, with the weights applied, conducting an LCA on nationally representative data allow the findings to be generalizable to over 2 million public school teachers in 2009.

My findings are aligned to the qualitative work of Mama and Hennessy (2013). In their study, they uncover four different types of technology-using teachers, while also finding that teacher beliefs and attitudes are important indicators for the different types of technology-using teachers. However, the present study differs in two key ways. First, the scope of Mama and Hennessy (2013) only focuses on using attitudes and beliefs to create their typology of teachers who use information and communication technologies (ICTs). In my full LCA model, I not only include teacher dispositions toward technology, but I also include teacher-centered use of technology, teacher directed student uses of technology, and preparation to use technology, provided the opportunity to find four statistically significant groups of technology-using teachers. This allowed me to understand differences across all four groups in more dynamic ways than just their attitudes and beliefs. The second difference between the present study and the Mama and Hennessy (2013) study is the proportion of teachers belonging to each subgroup. The present study shows a nationally representative ratio of technology-using teachers: Assessors (28.4%), Dexterous (24.4%), Presenters (24.8%), Evaders (22.2%). While the Mama and Hennessy (2013) study provides rich descriptions and describes the essence of the lived
experience of eleven technology-using teachers within one school, the ratios of teachers in each subgroup are not generalizable on a larger scale. My study extends this work on technology-using teachers to the entire population of U.S. public school teachers, identifying a concrete ratio of different types of teacher users. This again raises important considerations in using a larger sample size ($n = 2,764$) from a nationally administered dataset.

My findings are also congruent with the four-user typology in the Donnelly et al. (2011) study. In their work, the authors describe four different subgroups of teachers divided by their assessment practices. A significant body of research (Ertmer, 2005; Ertmer & Ottenbreit-Leftwich, 2010; Ravitz, Becker, & Wong, 2000; Zhao, Pugh, Sheldon, & Byers, 2002) points out that effective technology-using teachers tend to have a more learning, student-centered approach toward learning, as opposed to an assessment or teacher-focused centered approach. Like the findings in Donnelly et al. (2011), my findings show that the largest variance among the four significantly different subgroups of teachers lies in how they use technology for themselves and for their students (see Figure 2-2). While Dexterous and Presenter teacher types reported higher usage of student-centered approaches toward technology (i.e., making presentations, conducting research, developing multimedia, creating art and webcasts), Evaders and Assessors teacher subtypes used more teacher-centered approaches (i.e., administering tests, drill and practice programs, solving problems). While the Donnelly et al. (2011) study present rich descriptions of a typology, again, the present study tests this hypothesis with a larger sample of teachers and provides a nationally generalizable proportion of teachers who belong to each one of the subgroups with a particular propensity for certain pedagogical approaches with technology.

This study also sheds light on the critical issue of examining the debate about the impact of technology and teacher technology use through a social justice lens. As described earlier, the
results of the study show that socioeconomic status (see Table 2-4) significantly predicted a teacher’s membership in two of the subgroups in national data. I found that technology-using teachers in schools with more than half of the students on free or reduced lunch were 1.36 times more likely to be an Assessor than a Dexterous teacher. Likewise, in these same schools, teachers were less likely to be a Presenter than a Dexterous teacher. In light of these seemingly contradictory findings, I revisit this notion of a “new digital divide” that perpetuates gross inequities “in [the] differential ability” (Warschauer & Matuchniak, 2010, p. 213) to effectively use technology in teaching, learning, and leading in certain types of schools (Valadez & Duran, 2007; Warschauer, 2003; Warschauer et al., 2004). While it is outside of the scope of this study to explain why teachers in low-income schools have higher odds of belonging to these two groups, the findings push the concerted effort nationwide to close the “new digital divide” through teacher professional development that focus on more hands-on, project-based applications of technology that encourage critical thinking and deeper understanding of content (Ertmer et al., 2012; Mostmans, Vleugels, & Bannier, 2012; Ravitz et al., 2000; Vannatta & Beyerbach, 2000). Through emphasizing more student-centered approaches, how teachers use new technologies could align with high-impact instructional best practices that use social justice pedagogies to affirm, validate, and celebrate all students’ personal identities and life experiences (O’Hara, Pitta, Pritchard, & Webb, 2016). These findings also challenge the assumptions of technological determinism, or the idea that the introduction of technology alone is sufficient enough to determine pedagogical or cultural change, held by some by school leaders (Webster, 2017). Even in a sample where all respondents report that they use technology, the findings show how contextual variables pertaining to access, knowledge, and school culture influence the types of technology-using teachers. To investigate the impact of technology through this sociocultural
framework over time, I encourage the development of more robust, nationally representative survey instruments on teacher and school leader use of educational technology in schools as research looks to use nationally representative, quantitative data to address prevailing questions about equity, teaching, technology, and school change.

**Limitations**

While I argue that the results of my study are significant, I recognize that the study is limited in five key ways. First, the data collected on teachers’ use of educational technology were collected in early 2009. Given that how teachers use digital tools is constantly shifting and evolving, I recognize that the data collected in one given year might not fully represent how teachers are using technology in the classroom at any time before or after 2009. However, I used the FRSS 95 dataset because it was the most recent, nationally generalizable survey available from the National Center of Education Statistics, which provides information on teacher computer use, number of technology resources, and teachers’ perspective on technology-based professional learning. I encourage the collection of additional nationally representative data in order to capture the more current trends in school technology implementation efforts. Second, the sample size of the study ($n = 2,764$) while one of the largest used to date in considering subgroups of technology use, is relatively small due to the limited nature of the FRSS 95 sampling procedures. In the future, alternative national datasets with larger samples should be analyzed to continue identifying subgroups in technology-using teachers with a higher degree of statistical power to identify small to moderate effect size differences between these groups. Third, the results of the LCA yielded a strong model fit of at least four significantly different groups of technology-using teachers. However, in considering both fit statistics identified in the literature that determine the best model fit (Jung & Wickrama, 2008; Lo, 2005;
Lo et al., 2001; Masyn, 2013; Múthen, 2002), as well as the entropy (0.674) of the four-class model, there could be up to six different groups that can be identified in the data. Still, I am confident in my decision in interpreting the more parsimonious, four-class model due to the more conservative estimation of the LMR test and to avoid over-interpretation of the model. Fourth, robust variable selection within national datasets could provide a more complete picture of the types of teachers who use technology. My hope is that subsequent national surveys on teacher technology use would consider more research-based constructs when developing future instruments. Finally, although the findings are robust, I cannot address the question of why certain teachers belonged to certain groups or why certain external variables predicted membership in these subgroups. I encourage future research to address these critical questions about teacher technology users through other descriptive case studies.

Implications and Conclusions

My study reiterates the notion that technology-using teachers are not a monolithic group. The LCA identifies four statistically distinct groups of technology-using teachers that are generalizable to a population of U.S. public school teachers in 2009. Also, I found that the subgroups are not randomly distributed across school contexts, as low-income schools are more likely to have teachers who use technology in less meaningful ways. This propels the movement to advance a critical framework for technology use at the school and district levels that works to address digital inequity not only with what tools educators have, but what policies are developed to ensure that teachers and leaders are provided with the best professional supports and learning opportunities to learn how to use technology in ways that promote critical thinking, empower students’ identities, and validate students’ voice and perspectives as part of the learning process (Jenkins, Ito, & boyd, 2016; Livingstone, 2004).
The present study has several implications for actionable improvement in research, policy, and practice in educational technology. This new approach to exploring technology user typologies has implications for the development of educational technology products, as well as how educational technology companies market the technologies they offer to teachers and school leaders. Wind and Bell (2008) explain that markets are inherently heterogeneous and that companies use market segmentation as a strategy to appeal to different contexts and clients. In marketing terms, market segmentation is a strategy that separates “the market into homogeneous segments [in order to] understand of the needs and wants of these segments [and]…the development of marketing strategies to effectively research the target segments” (p. 222). The benefit of market segmentation as a strategy is that it helps companies tailor their products or services to their customers’ needs and wants, collect data on the segments and the contexts in which they operate, and map out processes and capabilities that could help project segment growth or change (Wind & Bell, 2008). Pertaining to the educational technology marketplace, the sheer amount of available tools can be overwhelming and confusing for many decision makers (Lindl, 2017). The typology presented in this study, as well as latent class analysis as a quantitative methodology, can inform the marketing strategy that educational technology companies use to market to schools or to provide professional development for different types of teachers who decide to use their products. Likewise, as districts and school leaders work to understand the types of teachers they serve, they can implore educational technology companies to show them the extent to which the products they offer appeal to different types of technology-using teachers.

My study also has strong implications for how leaders approach technology leadership in schools in three ways. First, as modern conceptions of leadership for learning (Boyce & Bowers,
2018; Hallinger, 2011; Murphy, Elliott, Goldring, & Porter, 2007; Paletta, Alivernini, & Manganelli, 2017) theorize leadership is not a function of one individual, but rather a series of leadership roles, this typology of technology-using teachers can help school leaders identify certain characteristics of individuals that can act as teacher leaders based on their own vision for technology integration in their schools.

Second, because the findings are nationally generalizable, leaders can use this typology as a starting point with teachers as he or she pushes teachers toward their growing edge in what they were taught to do and what they actually do in the classroom with technology (Pope, Hare, & Howard, 2002). Because the full LCA model accounts for multiple indicators of teacher technology use, the findings reveal critical gaps in how certain teachers use technology, allowing leaders to build organizational processes and learning opportunities that support teachers as they develop the specific knowledge and skills they need to grow, while also considering how context influences their use. I encourage further multilevel latent class analysis (Bowers et al., 2017; Henry & Muthén, 2010; Urick & Bowers, 2014) that nests these subgroups of technology-using teachers within schools with certain types of leaders to further explore the extent to which different types of principals and leaders influence the teacher technology types.

Third, Zhao et al. (2004) note that when educators only envision “technology [as] just a tool, a means to an end” (p. 1), this belief can have detrimental implications for educational practice. Promoting this values neutral conception of technology “gives teachers a false sense of empowerment, as well as a feeling of guilt when they do not achieve their intended goals…[technology] comes with shapes and expectations” (Zhao et al., 2004, p. 1). Aligned with notions of culturally responsive teaching and leadership (Khalifa, Gooden, & Davis, 2016), the findings from this study confront the belief that many school leaders have that technology tools
are socially neutral entities that can be utilized with one approach across time, contexts, and individuals (Biraimah, 1993; Furr, Ragsdale, & Horton, 2005; Gorski, 2009; Kruger-Ross, 2013; Webster, 2017). As such, school leaders who remain fixated on describing technology as “just a tool” becomes difficult to justify. As technology leaders at the school and district levels make decisions to purchase and promote certain classroom technologies, it is imperative for leaders to understand that the tools themselves propagate expectations for teacher usage, just as much as context influences technology use. Seeing that two of the four groups of technology-using teachers in my study (Presenters and Assessors) utilize technology for distinct pedagogical purposes, I implore school leaders to circumspectly select new technologies that align to the vision for teaching and learning they expect to see in classrooms, particularly in schools that where contexts can influence how teachers use technology. For example, does purchasing and installing stationary, interactive whiteboards actually encourage Presenter teachers to use technology in active, student-centered ways? Do one-to-one laptop programs promote teacher growth in a school of Evaders or Presenters? I position this study as a practical, empirically-based typology framework for school and district leaders to use as they purchase new technology tools, as well as a conceptual framework for research and evaluation studies that examine the extent to which school or district technology expenditures influence the types of technology-using teachers and leaders that exist at the individual, school, or district levels. Furthermore, this study also raises larger conceptual questions pertaining to the extent to which technology leadership should be viewed through the lens of social justice and cultural responsiveness leadership (see Chapter 4, this volume).

The typology described throughout this paper also reiterates the need for data-driven professional learning experiences for technology-using teachers that are situated to address the
needs in their school contexts (Bauer & Kenton, 2005; Lawless & Pellegrino, 2007; Meier, 2005; Mouza, 2009). Prior research argues that technology professional development cannot assume homogeneity of teachers’ skill levels and competencies with technology (Brinkerhoff, 2006; Hughes & Ooms, 2004; Mouza & Wong, 2009; Phillips, Desimone, & Smith, 2011; Swan et al., 2002). In designing new professional learning opportunities, there is also a renewed call for school leaders to use data for evidence-based improvement in professional learning (Bowers, Shoho, & Barnett, 2014; Cho & Wayman, 2014). Thus, the use of latent class analysis in the study provides a useful and innovative methodological approach toward evidence-based technology professional development that focuses on building the capacity and skills of the teacher starting from their current practice. I imagine that district data leaders can utilize latent class analysis as a means to help identity sustained opportunities for professional development for teachers and encourage teachers in the same subgroup, or even different groups, to participate in highly customized, evidence-based professional learning communities.

In examining teacher technology use as a multifaceted construct (Bebell et al., 2004), this study presents a clearer picture of teacher technology use and has several implications for the development of future policy interventions in education technology policy. In examining district-level policy for teacher technology use, Culp et al. (2003) found that policy makers tend to use three predetermined rationales to warrant the increased investment of instructional technology, such as envisioning technology as a tool for addressing challenges with teaching and learning, using technology as a change agent for instructional practice, and promoting technology as a central force in economic competitiveness (Culp et al., 2003, pp. 5-6). While these rationales are notable in light of the increased emphasis on digital age learning (U.S. Department of Education, 2016), schools continue to suffer from an implementation problem when addressing certain
barriers to sustaining technology integration efforts (Ertmer, 1999; Hsu, 2016; Kopcha, 2012). It is easy to see that many of the policies concerning educational technology are implemented using an ineffective “forward mapping approach,” where policies are created and then implemented by policy makers without the input of the individuals on the ground level in its planning and execution (Elmore, 1980). Forward-mapped policy implementation can result in confusion, error, and obscurity on the ground level (Elmore, 1980). The nationally generalizable typology of four significant different subgroups of technology-using teachers, along with usage indicators of each type and predictive variables, can provide policy makers with a starting point as they create more person-centered, grassroots instructional technology policy interventions that evolve based on the characteristics and needs of the lowest level of implementation, or teachers in schools. My findings, along with a “backward mapping” approach toward policy (Elmore, 1980), could help transform district-level decision making strategies as they develop policy instruments pertaining to resource allocation, teacher evaluation, teacher professional development, and teacher and principal preparation programs that better support the growth of various types of technology-using teachers and leaders.

While this study simply shows what types of technology-using teachers exist, rather than how or why these variables interact to influence teacher technology use, I maintain that this present study is the start of many important contributions to the field of educational technology and educational leadership as it is one of the only studies to quantitatively examine teacher technology user types with nationally representative data while also building on prior qualitative research that poignantly address the existing questions and complexities of understanding teacher technology use in schools.
References


### Appendices

**Appendix 2-A: Descriptive Statistics of Indicator Variables from FRSS 95**

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>N</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>FRSS 95 Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Use of technology for instruction</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Making presentations</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.664</td>
<td>0.472</td>
<td>Q6G; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td>Administering tests</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.455</td>
<td>0.498</td>
<td>Q6H; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td>Drill, practice programs, tutorials</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.525</td>
<td>0.499</td>
<td>Q6J; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td><strong>Preparation to use technology</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Professional learning activities</td>
<td>2,675</td>
<td>0</td>
<td>1</td>
<td>0.951</td>
<td>0.215</td>
<td>Q9C; 0=Not at all, 1=To some extent</td>
</tr>
<tr>
<td>Training from technology staff</td>
<td>2,675</td>
<td>0</td>
<td>1</td>
<td>0.943</td>
<td>0.232</td>
<td>Q9D; 0=Not at all, 1=To some extent</td>
</tr>
<tr>
<td>Independent learning</td>
<td>2,705</td>
<td>0</td>
<td>1</td>
<td>0.979</td>
<td>0.142</td>
<td>Q9E; 0=Not at all, 1=To some extent</td>
</tr>
<tr>
<td><strong>Disposition toward professional learning</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technology PD met goals</td>
<td>2,446</td>
<td>0</td>
<td>1</td>
<td>0.824</td>
<td>0.381</td>
<td>Q11A; 1=Agree or strongly agree</td>
</tr>
<tr>
<td><strong>Use of technology for productivity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Email or listserv with parents</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.599</td>
<td>0.490</td>
<td>Q8A1; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td>Email or listserv with students</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.252</td>
<td>0.434</td>
<td>Q8A2; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td>Student record management</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.807</td>
<td>0.395</td>
<td>Q6D; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td><strong>Teacher-directed student use of technology for discrete skills</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Preparing written text</td>
<td>2,498</td>
<td>0</td>
<td>1</td>
<td>0.633</td>
<td>0.482</td>
<td>Q7A; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td>Learning/practicing basic skills</td>
<td>2,573</td>
<td>0</td>
<td>1</td>
<td>0.699</td>
<td>0.459</td>
<td>Q7C; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td>Conducting research</td>
<td>2,545</td>
<td>0</td>
<td>1</td>
<td>0.688</td>
<td>0.464</td>
<td>Q7D; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td>Solving problems, analyzing data, performing calculations</td>
<td>2,237</td>
<td>0</td>
<td>1</td>
<td>0.466</td>
<td>0.499</td>
<td>Q7H; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td><strong>Teacher-directed student use of technology for hands-on tasks</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Developing and presenting multimedia presentations</td>
<td>2,348</td>
<td>0</td>
<td>1</td>
<td>0.450</td>
<td>0.498</td>
<td>Q7J; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td>Creating art, music, movies, or webcasts</td>
<td>2,159</td>
<td>0</td>
<td>1</td>
<td>0.266</td>
<td>0.442</td>
<td>Q7K; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
<tr>
<td>Conduct experiments or perform measurements</td>
<td>2,067</td>
<td>0</td>
<td>1</td>
<td>0.266</td>
<td>0.442</td>
<td>Q7I; 0=Never/Rarely, 1=Sometimes/Always</td>
</tr>
</tbody>
</table>

*N* 2,764
Appendix 2-B: Descriptive Statistics of Covariates from FRSS 95

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>FRSS 95 Variable</th>
</tr>
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<tbody>
<tr>
<td><strong>School urbanicity:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>City</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.216</td>
<td>0.412</td>
<td>URBAN; 1=City</td>
</tr>
<tr>
<td>Town</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.145</td>
<td>0.350</td>
<td>URBAN; 1=Town</td>
</tr>
<tr>
<td>Rural</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.302</td>
<td>0.459</td>
<td>URBAN; 1=Rural</td>
</tr>
<tr>
<td><strong>School type:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elementary</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.588</td>
<td>0.492</td>
<td>LEVEL; 1=Elementary school</td>
</tr>
<tr>
<td><strong>Enrollment:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small (less than 300)</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.124</td>
<td>0.329</td>
<td>SIZE; 1=Less than 300</td>
</tr>
<tr>
<td>Large (more than 1000)</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.258</td>
<td>0.438</td>
<td>SIZE; 1=300 to 999</td>
</tr>
<tr>
<td>More than 50% of students</td>
<td>2,764</td>
<td>0</td>
<td>1</td>
<td>0.434</td>
<td>0.496</td>
<td>POVST; 1=More than 50%</td>
</tr>
<tr>
<td>eligible for free or reduced</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>lunch</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of computers in classroom</td>
<td>2,764</td>
<td>0</td>
<td>33</td>
<td>4.47</td>
<td>5.819</td>
<td>Q1A1_TOP</td>
</tr>
<tr>
<td>Years of teaching experience</td>
<td>2,764</td>
<td>1</td>
<td>41</td>
<td>13.83</td>
<td>9.797</td>
<td>Q15_TOP</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2,764</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix 2-C: MPlus Code for Three-Step Latent Class Analysis (LCA)

TITLE: Teacher Technology Use LCA, FRSS 95 2009

DATA: FILE = "C:\Users\keg2132\Documents\InUseDataFiles\FRSS95_CLEAN.dat" ;

VARIABLE:
  NAMES = ID Q6G_R Q6H_R Q6J_R Q9C_R  
  Q9D_R Q9E_R Q11A_R Q8A1_R Q8A2_R Q6D_R  
  Q7A_R Q7C_R Q7D_R Q7H_R Q7J_R Q7K_R  
  Q7I_R CITY TOWN RURAL POVST_R ELEM  
  SEC SMALL MEDIUM YRSEXP COMPS TFWT ;
  MISSING = ALL(9999) ;
  WEIGHT = TFWT ;
  IDVARIABLE = ID ;
  USEVARIABLES = Q6G_R Q6H_R Q6J_R Q9C_R  
  Q9D_R Q9E_R Q11A_R Q8A1_R Q8A2_R  
  Q6D_R Q7A_R Q7C_R Q7D_R Q7H_R Q7J_R  
  Q7K_R Q7I_R ;
  CATEGORICAL = Q6G_R Q6H_R Q6J_R Q9C_R  
  Q9D_R Q9E_R Q11A_R Q8A1_R Q8A2_R  
  Q6D_R Q7A_R Q7C_R Q7D_R Q7H_R Q7J_R  
  Q7K_R Q7I_R ;
  CLASSES = c(4) ;
  AUXILIARY =  
    (R3STEP) CITY TOWN RURAL POVST_R ELEM  
    SEC SMALL MEDIUM YRSEXP COMPS ;

ANALYSIS:
  TYPE = MIXTURE ;
  PROCESSORS = 8 (STARTS) ;
  MITERATION = 5000 ;
  STARTS = 25000 250 ;
  STITERATIONS = 100 ;

OUTPUT:
  SAMPSTAT STANDARDIZED TECH11 ;

PLOT:
  TYPE = plot3 ;
  SERIES = Q6G_R Q6H_R Q6J_R Q9C_R  
  Q9D_R Q9E_R Q11A_R Q8A1_R Q8A2_R  
  Q6D_R Q7A_R Q7C_R Q7D_R Q7H_R Q7J_R  
  Q7K_R Q7I_R (*) ;

SAVEDATA:
  SAVE = CPROBABILITIES ;
  FILE = CPROBS-KEG-001.DAT ;
  FORMAT = FREE ;
  ESTIMATES = MIXEST-001.DAT ;
Chapter III – ARTICLE TWO

“Is School and District Technology Leadership ‘Just Good Leadership’? A Multilevel Latent Class Analysis (MLCA) of the 2011-12 Texas School Technology and Readiness (STaR) Charts”

Abstract

Purpose: The purpose of this study is to investigate leadership at the school and district levels from a new conceptual and empirical lens by examining perceptions of technology leadership from population-level data in the 2011-12 Texas School Technology and Readiness (STaR) Charts. Researchers often describe technology leadership as just good leadership, but understanding the extent to which technology leadership can provide unique insights into the opportunities and challenges of 21st Century leadership practice could be helpful in evaluating new technology-focused instructional reforms and their impact on student achievement. Method: Using multilevel latent class analysis (MLCA) on school and district level data from the 2011-12 STaR Charts, I investigate the extent to which there is a typology of schools (n = 6,935) and the extent to which school-level subgroups are distributed across different subgroups of Texas districts (n = 912). I also investigate the extent to which demographic variables influence the school and district subgroups and perform a post hoc ANCOVA to determine whether aggregate pass rate percentages on the 2012 State of Texas Assessment of Academic Readiness (STARR) and the Texas Essential Knowledge and Skills (TEKS) tests significantly differ across the district and school subgroups. Findings: I find three statistically significant school-level subgroups, High STaR Schools (29.4%), Moderate STaR Schools (42.3%), and Low STaR Schools (28.2%), and four district-level subgroups, Model STaR Districts (19.8%), High STaR Districts (22.8%), Moderate STaR Districts (42.3%), and Low STaR Districts (22.6%). My findings also indicate that the STaR Chart multilevel typology model had a significant and independent effect on
school and district pass rate percentages on the 2012 Texas STARR/TEKS standardized tests, with the *High STaR Schools* having statistically significantly higher pass rates on the 2012 Texas STARR/TEKS standardized tests and the *Low STaR Districts* subgroups having statistically significantly lower pass rates on the 2012 Texas STARR/TEKS standardized tests. I also show that schools with higher percentages of historically disadvantaged students were more likely to be in *Low STaR Schools* and that these schools had the lowest pass rate percentage on the 2012 Texas STARR/TEKS standardized tests. Similarly, the school subgroups were disproportionately distributed across the district subgroups with *Low STaR Districts* being more likely to have schools with higher proportions of African-American and Hispanic students and have the lowest pass rate percentage on the 2012 Texas STARR/TEKS standardized tests. **Implications:** As the first multilevel typology study on school and district-level technology leadership with large-scale data from Texas, the present study provides empirical evidence to suggest that *strong technology leadership is indeed good leadership* within one of the most diverse locales in the U.S. However, these findings also suggest that good technology leadership is not randomly distributed across different schools and districts. This study has strong implications for the development of a new leadership conception of *technology leadership for social justice* that promotes instructional improvement through technology, while also pushing school and district leaders to adopt more culturally responsive leadership processes that temper the consequences of digital and educational inequity in historically disadvantaged schools, districts, and communities.
Introduction

The purpose of this study is to investigate K-12 leadership at the school and district levels in the United States from a new perspective by examining perceptions of school and district technology leadership from a large-scale dataset, the 2011-12 Texas School Technology and Readiness (STaR) Charts. In pursuit of new policy reforms to improve classroom instruction, recently, school and district leaders have invested in the promise of educational technology as “a powerful tool for transforming learning…[that] can reinvent approaches to learning and collaboration, [and] shrink long-standing equity and accessibility gaps” (U.S. Department of Education, 2017, p. 3). However, as critics continue to challenge the idealized perception that technology alone can change the core of teaching and learning (Bulman & Fairlie, 2016; Sanders & George, 2017), especially within historically minoritized communities where digital inequities are rampant (Gorski, 2002, 2005, 2008; Normore & Lahera, 2018; Warschauer, 2016), there is a renewed commitment to better understand school and district leadership in order to mitigate the challenges of school improvement efforts in the digital age.

Literature Review

School and District Technology Leadership Research

In the late 1980s and early 1990s, position papers in several educational technology peer-reviewed journals began to define a new form of school and district leadership for the digital age of schooling. Scholars referred to this emergent leadership practice as school and district technology leadership. At its conceptual beginnings, scholars defined technology leadership as the specific administrative tasks and technological competencies that school and district leaders should possess. Within these early frameworks, school and district leaders were expected to demonstrate competency with several technology-related tasks, such as maintaining school
records with computers, developing technology-based student assessment, emailing, reviewing of hardware and software, and seeking grants through funding sources (Bozeman & Spuck, 1991; Kearsley, 1988; Kearsley & Lynch, 1992; Thomas & Knezek, 1991). However, while these frameworks assisted administrators who were technology early adopters in the 1990s, by the turn of the century, educators and policy makers soon realized that effective technology leadership required a shift in management skills, leadership processes, and school culture (Fullan, 2007).

Consequently, in 2001, the International Society of Technology in Education (ISTE) developed the National Education Technology Standards for Administrators (NETS-A) as one example of a national effort to reposition technology leadership as an emerging framework in how leaders can support instructional change at the school and district levels (ISTE, 2009). The most recent version of ISTE NETS-A Standards (2018) lay out five key technology leadership roles for school and district administrators: (1) equity and citizenship advocate, (2) visionary planner, (3) empowering leader, (4) systems designer, and (5) connected learner. For educators and researchers alike, the development of the ISTE NETS-A Standards represented a new conception of technology leadership that moved away from simply defining technology leadership as an set of technology-related administrative tasks for leaders toward integrating technology leadership behaviors within the larger educational leadership literature landscape (McLeod & Richardson, 2011; Richardson, Bathon, Flora, & Lewis, 2012). In fact, to date, the NETS-A Standards remain the most widely used technology leadership conceptual framework in the technology leadership research literature and in technology leadership professional learning programs for school and district leaders (Anderson & Dexter, 2005; Crompton, 2014; Gibson, 2002; McLeod & Richardson, 2011; Richardson et al., 2012; Yu & Durrington, 2006).
Many of the research findings within the technology leadership research that use the NETS-A Standards as its conceptual framework mirror the research findings within several prominent educational leadership theories. Like research findings anchored in transformational leadership theory (Bass & Avolio, 1990, 1993; Hallinger, 1992; Leithwood, 1992; Leithwood & Sun, 2012) that espouse that leaders improve schools through cultivating positive relationships, several technology leadership research studies also find that effective school and district technology leaders empower educators to adopt innovative resources and pedagogies (Afshari, Bakar, Luan, & Siraj, 2012; Moolenaar, Daly, & Sleegers, 2010) and build strong relationships with the community in-person or through online social media networks (Blau & Presser, 2013; Cox & McLeod, 2014; McLeod, Richardson, & Sauers, 2015; Sauers, Richardson, & McLeod, 2014). In a similar manner, while key educational leadership theories, like shared instructional leadership (Marks & Printy, 2003; Printy, Marks, & Bowers, 2009; Robinson, Lloyd, & Rowe, 2008) and leadership for learning (Boyce & Bowers, 2018b; Hallinger, 2011; Hallinger & Heck, 2010; Murphy, Elliott, Goldring, & Porter, 2007), argue that school and district leaders in both formal and informal roles should collectively focus on leadership behaviors that influence teaching and learning, several technology leadership research studies also argue that effective school and district technology leaders know how to craft a vision for technology (Levin & Schrum, 2013; McLeod et al., 2015; McLeod & Richardson, 2013; Richardson, McLeod, & Sauers, 2015; Sauers et al., 2014), make curricular choices to support meaningful technology use (Ausband, 2006; Dexter, Seashore-Louis, & Anderson, 2009), and share the responsibility of technology leadership with other leaders, including teachers, instructional coaches, district administrators, and technology support staff (Dexter, 2011; Dexter et al., 2009; Hughes, Boklage, & Ok, 2016). On the whole, as technology leadership research runs parallel to research
in the larger educational leadership literature, and as policy makers position technology leadership as a core competence for school and district leaders, a strong assumption has emerged that “good technology leadership is essentially just good leadership for the digital era” (Richardson et al., 2015, p. 15).

**Theoretical and Methodological Tensions within the Technology Leadership Literature**

However, to what extent is there strong empirical evidence that technology leadership is just good leadership? Recent critiques of the technology leadership research literature raise three tensions related to this assumption. First is the fact that almost all of the most recent literature reviews on technology leadership conclude that school and district technology leadership remains understudied and undervalued in the larger educational leadership discipline (Dexter, Richardson, & Nash, 2016; McLeod & Richardson, 2011; Richardson et al., 2012; Richardson & Sterrett, 2018). In recent studies that examine the major theories and concepts that have shaped the educational leadership field in the last five decades, technology leadership is notably absent (Wang, 2018; Wang & Bowers, 2016; Wang, Bowers, & Fikis, 2017). In fact, even within the body of technology leadership research, several scholars have noted that research studies focusing on the five ISTE Standards (2018) have been largely uneven with limited research on the standards related to how leaders understand issues of equity, ethics, and social issues in technology leadership (McLeod & Richardson, 2011; Richardson et al., 2012). In all, even in light of the technology-focused reform in the last decade, Richardson and Sterrett (2018) urge that there is still “a dire need to better understand the intersection of K-12 school leadership and technology” (p. 591).

The second critique that challenges the assumption in the technology leadership literature that technology leadership is simply good leadership is that the NETS-A Standards (ISTE, 2009),
one of the most widely used conceptual frameworks in technology leadership research, resembles a laundry list of technology leadership behaviors without an underlying theory undergirding its application. Within the larger body of educational leadership literature, a common critique of leadership frameworks, like Marzano Balanced Leadership (Waters, Marzano, & McNulty, 2004), has been that these leadership frameworks are largely atheoretical and offer minimal insight into the order to perform the behaviors or into the varied ways in which different leaders perform these behaviors within their specific school contexts (Jacob et al., 2015). Urick (2016) hypothesizes that this type of “leadership style literature has provided a comprehensive list of potentially effective leadership behaviors but has not demonstrated the ways in which school leaders actually differ” (p. 449). In a similar manner, despite the wealth of technology leadership literature that uses the NETS-A Standards as its guiding conceptual framework, Sauers et al. (2014) still warn that technology leadership research “need[s] theoretical models and concrete actionable ideas that can guide practitioners and researchers” (p. 1182). Because “theories serve as a guide to action, collecting facts, generating new knowledge, and explaining the nature of educational leadership” (Wang, 2018, p. 2), some have argued that the lack of theory-driven research hurts the technology leadership field in that research findings give little insight for school leaders into what order to perform the technology leadership behaviors, how different types of leaders adjust their technology leadership based on their circumstances or contexts, or even understanding the ways in which these technology leadership behaviors impact student achievement outcomes across diverse a wide range of schools and districts (McLeod & Richardson, 2011; Sauers et al., 2014).

The third reason that researchers hypothesize that the technology leadership literature is disconnected from the larger educational leadership literature is that the body of school and
district technology leadership research literature contains very few empirical studies that use large-scale data and robust methodologies to explore perceptions of technology leadership that are generalizable to a larger population. Much of the research on school and district technology leadership focuses on descriptive case studies of new technology initiatives (Hughes et al., 2016), leadership practices of exemplary teachers and leaders within a school or district (Levin & Schrum, 2012, 2013, 2014), or award-winning, “technology-savvy” superintendents (Cox & McLeod, 2014; Richardson et al., 2015; Sauers et al., 2014). Yet, according to Sauers et al. (2014), focusing only on descriptive studies is problematic because “knowledge about effective technology leadership remains scant and primarily anecdotal” (p. 1182). To this end, as these three theoretical and methodological tensions complicate how the technology leadership literature fits within the larger educational leadership field, there is a need for more research studies that utilize technology leadership as a theoretical lens to advance new theory-driven conceptual frameworks of leadership and that employ robust methodologies with large-scale data to more deeply understand the link between technology and leadership (Schrum & Levin, 2016).

**School Technology and Readiness (STaR) Charts**

Large-scale data collected at the state level present a unique opportunity to explore leadership practice from the lens of technology leadership and to analyze population-level data that could have noteworthy implications for research, policy, and practice in technology leadership. Currently, there are no nationally generalizable datasets on technology leadership. Even so, in the late 1990s, the CEO Forum on Education and Technology (1997), an advocacy group consisting of 21 business and educational leaders, including Steve Jobs, former CEO of Apple, and Anne Bryant, former executive director of the National School Boards Association, developed a survey instrument called the *School Technology and Readiness (STaR) Charts* to
help U.S. schools and districts assess their progress in advancing educational technology in classrooms and to help “develop an educational plan that is firmly rooted in education objectives and […] ensure[s] efficient allocation of resources” (p. 4). The CEO Forum on Education and Technology (1997) further articulates the mission of the STaR Chart Assessment in their first policy report:

The STaR Chart is intended to be a guide, not a definitive measure of a school’s effective use of classroom technology. A particular school may find that it falls well within one category based on some indicators, and squarely into another category based on others. Such a mixed reading can be expected because every school is unique. The STaR Chart is intended to inform, providing educators and administrators in American schools with information about how schools compare to typical American schools and to provide information that may help ensure that the student have the best change to benefit from educational technology. (p. 4)

In addition to this aim, the original 1997 STaR Chart report also defines “Four Pillars” (CEO Forum on Education and Technology, 1997, p. 14) that the Clinton & Gore Administration in the 1990s outlined as key areas that school and district leaders should focus their technology leadership efforts. These four areas included hardware, connectivity, digital content, and professional development. Similarly to the first iteration of the NETS-A Standards in 2001 (ISTE, 2009), the report notes that the hardware and connectivity pillars assess how school and district leaders improve technology infrastructure and access to computers, while the digital content and professional development pillars assess the ability of leaders to acquire new digital resources and to support adult learning with technology (CEO Forum on Education and Technology, 1997). Future iterations of the STaR Chart surveys added integration and use as another pillar (CEO Forum on Education and Technology, 1999, 2000, 2001).

With the aim of understanding how schools use technology through more robust measures, The CEO Forum on Education and Technology (1997, 1999, 2000, 2001) administered a survey called the STaR Chart Assessment four times from 1997-2001 to over
80,000 U.S. schools in an attempt to collect nationally generalizable data on school and district technology readiness. The STaR Chart Assessment was developed using the eleven Technology Measure variables identified by the Quality Education Data (QED) group, a defunct marketing firm that regularly surveyed technology use in schools and districts (Becker, 1998; Becker, Wong, & Ravitz, 1998). Participating schools received a STaR index score ranging from 1 (lowest) to 7 (highest) based on their self-reported Technology Measures rating (CEO Forum on Education and Technology, 1997). The CEO Forum on Education and Technology (1997, 1999, 2000, 2001) then aggregated the data and generated a policy report on the findings.

Culp, Honey, and Mandinach (2003) note that The CEO Forum on Education and Technology (1997) released its last report on the nationally-administered STaR Chart Assessment in 2001. However, as interest in the national STaR Chart survey grew at the federal level, several state boards of education, including Florida (Florida Laptops for Learning Task Force, 2004), Massachusetts (Massachusetts Educational Technology Advisory Council, 2010), and Texas (Texas Education Agency, 2006), began to incorporate iterations of the STaR Chart into their state technology plans. In addition to the technology-focused “Four Pillars,” certain states, such as Texas, include several leadership variables in their version of the Charts. The Texas STaR Chart incorporates new STaR domains that reflect specific leadership behaviors outlined in research on leadership for learning theory, like managing human and material resources, providing professional development, and supporting curricular innovation (Boyce & Bowers, 2018b; Hallinger, 2011; Murphy et al., 2007).

The state-specific iteration of the STaR Charts in Texas asks teachers to rate technology leadership in four domains: (1) Teaching and Learning (TL), (2) Educator Preparation and Development (EP), (3) Leadership, Administration, and Instructional Support (L), and (4)
Infrastructure for Technology (INT). The Teaching and Learning (TL) domain is aligned with research that finds that principals can influence teacher technology use (Chang, Chin, & Hsu, 2008; Coffland & Strickland, 2004; Dawson & Rakes, 2003) and asks teachers about their patterns of technology use, frequency of digital content, and student mastery of the Texas Essential Knowledge and Skills for Technology Application Standards (Texas Education Agency, 2015). In the Educator Preparation and Development (EP) domain, respondents rate the frequency and quality of the professional development, mirroring research findings that argue that quality technology professional development should align to school or district instructional goals (Lawless & Pellegrino, 2007; Schwanenberger et al., 2013). Further, studies show effective technology leadership is a core part of technology-focused instructional reform (Anderson & Dexter, 2005). Therefore, the Leadership, Administration, and Instructional Support (L) domain focuses on teachers’ perceptions of specific technology leadership behaviors, like vision building, resource allocation, human resource management, and communication. Finally, as the access and quality of the technology infrastructure is directly associated with teachers’ and leaders’ attitude toward using technology in schools (An & Reigeluth, 2011; Kopcha, 2012), the Infrastructure for Technology (INT) asks teachers to rate their school’s technology infrastructure.

Conceptually, the Texas STaR Chart domains mirror behaviors outlined in leadership for learning theory and many of the domains of the Comprehensive Assessment of Leadership for Learning (CALL) Survey (Blitz, Salisbury, & Kelley, 2014; Bowers et al., 2017; Halverson & Kelley, 2017; Halverson, Kelley, & Shaw, 2014; Kelley & Halverson, 2012). In comparison to other prominent surveys in educational leadership, like the Vanderbilt Assessment of Leadership in Education (VAL-ED) survey (Porter et al., 2010), that focus primarily on principal leadership behaviors (Goff, Salisbury, & Blitz, 2015), in 2009, researchers at the University of Wisconsin-
Madison received a $1.6 million federal grant from the Institute of Education Sciences (IES) to develop an empirically-validated survey that measures leadership for learning behaviors through a distributed, shared leadership framework and attempts to capture both teachers’ and leaders’ perceptions of leadership tasks and behaviors (Blitz et al., 2014; Bowers et al., 2017; Halverson & Kelley, 2017; Halverson et al., 2014; Kelley & Halverson, 2012). The CALL survey captures perceptions of leadership for learning in five domains that are similar to the STaR Chart surveys: (1) Focus on Learning, (b) Monitoring Teaching and Learning, (c) Building Nested Learning Communities, (d) Acquiring and Allocating Resources, and (e) Maintaining a Safe and Effective Learning Environment (Blitz et al., 2014; Bowers et al., 2017; Halverson et al., 2014; Kelley & Halverson, 2012). While the Focus on Learning and Monitoring Teaching and Learning strands are based in research that finds that leaders, in formal or informal roles, can indirectly impact student achievement by focusing on instructional leadership behaviors tied to teaching and learning (Hallinger, 2011; Hallinger & Heck, 1998, 2010; Hallinger & Murphy, 1985; Heck & Hallinger, 2014; Robinson et al., 2008), the Building Nested Learning Communities and Acquiring and Allocating Resources strands note that the leaders must attend to the managerial duties of leadership, while also cultivating a vision within the school community (Boyce & Bowers, 2018b; Hallinger, 2011; Murphy et al., 2007).

Interestingly, there is no alignment between CALL Domain 5: Maintaining a Safe and Effective Learning Environment and the Texas STaR Charts, as well as between the Texas STaR Chart Domain INF: Infrastructure for Technology and the CALL survey domains. This slight misalignment between the two surveys not only reinforces the need to integrate technology leadership into the conceptions of leadership for learning in the larger body of instructional leadership literature that explores the link between leadership and student achievement, but it
also could suggest that the body of technology leadership research undervalues collecting data that will allow researchers to examine multiple perceptions of leadership practice and the different organizational contexts in which leadership is enacted (Boyce & Bowers, 2018a; Hallinger & Heck, 2011; Marks & Printy, 2003; Printy et al., 2009; Urick & Bowers, 2014b). Table 3-1 describes each of the Texas STaR Chart domains and provides the parallel domains and subdomains from the CALL survey.
Table 3-1. Specification of Alignment between the 2011-12 Texas STaR Chart Domains and the CALL Survey Domains

<table>
<thead>
<tr>
<th>2011-12 Texas STaR Chart Domain and Description</th>
<th>Texas STaR Chart Survey Indicators</th>
<th>Aligned CALL Survey Domain and Subdomains*</th>
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<tbody>
<tr>
<td><strong>TL – Teaching and Learning:</strong> focuses on teachers’ perceptions of applications of technology in classroom instruction, in various content areas, and in the state standards</td>
<td>TL1: Patterns of classroom use</td>
<td>Domain 1: Focus on Learning</td>
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<td>TL2: Frequency/design of instructional setting using digital content</td>
<td>1.1. Maintaining a school-wide focus on learning</td>
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<td>TL3: Content area connections</td>
<td>1.2. Formal leaders as instructional leaders</td>
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<td>TL4: Technology applications (TA) TEKS implementation</td>
<td>1.3. Collaborative design of integrated learning plans</td>
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<td>TL5: Student mastery of technology applications (TA) TEKS</td>
<td>1.4. Providing appropriate services for students who traditionally struggle</td>
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<td>TL6: Online learning</td>
<td>Domain 2: Monitoring Teaching and Learning</td>
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<td><strong>EP – Educator Preparation and Development:</strong> focuses on teachers’ perception of technology competencies of teachers and patterns of use, along with participation in professional development</td>
<td>EP1: Professional development experiences</td>
<td>Domain 2: Monitoring Teaching and Learning</td>
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<td></td>
<td>EP2: Models of professional development</td>
<td>2.3. Formative evaluation of teaching</td>
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<td></td>
<td>EP3: Capability of educators</td>
<td>2.4. Summative evaluation of teaching</td>
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<td></td>
<td>EP4: Technology professional development participation</td>
<td>Domain 3: Building Nested Learning Communities</td>
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<td></td>
<td>EP5: Levels of understanding and patterns of use</td>
<td>3.1. Collaborative schoolwide focus on problems of teaching</td>
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<td></td>
<td>EP6: Capability of educators with online learning</td>
<td>3.2. Professional learning</td>
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<td></td>
<td><strong>INF – Infrastructure for Technology:</strong> focuses on teachers’ perception of the instructional environment and the tools and resources offered in the school</td>
<td>INF1: Students per classroom computers</td>
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<td></td>
<td>INF2: Internet access connectivity speed</td>
<td>4.1. Personnel practices</td>
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<td></td>
<td>INF3: Classroom technology</td>
<td>4.2. Structuring and maintaining time</td>
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<td></td>
<td>INF4: Technical support</td>
<td>4.3. School resources focused on student learning</td>
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<td></td>
<td>INF5: Local area network/wide area network</td>
<td>4.4. Integrating external expertise into school instructional program</td>
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<td></td>
<td>INF6: Distance learning capacity</td>
<td><strong>No clear alignment between STaR Charts and CALL.</strong></td>
</tr>
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</table>

*Note: There is no clear alignment between the CALL Domain 5: Maintaining a Safe and Effective Learning Environment and the Texas STaR Chart domains.

**Note: There is no clear alignment between the Texas STaR Chart Domain INF: Infrastructure for Technology and the CALL survey domains.
Given that the Texas STaR Chart survey domains are closely aligned to the CALL survey, a number of recent peer-reviewed studies and doctoral dissertations in educational leadership have used STaR Chart data to examine technology leadership behaviors and its impact on student achievement (Davidson, Richardson, & Jones, 2014; Dawson & Rakes, 2003; Lea, 2016; Mishnick, 2017; Moore & Serfin, 2017; Plyler, 2017; Tipton, 2015). Still, the outcomes of these studies are largely inconclusive. Related to teacher use, in a study focusing on teachers in all Texas middle schools, Lea (2016) found that teacher STaR Chart scores did not improve over three years in three of the four domains, but that higher teacher STaR Chart scores were positively correlated with student achievement in mathematics and reading. However, in similar studies exploring the correlation between teachers’ perceptions of technology integration and student achievement in one rural Texas school district (Moore & Serfin, 2017) and in 57 high schools in Texas ESC Region 7 (Tipton, 2015), both of the authors found no correlation between teachers’ perceptions of technology and student test scores. Studies examining principals’ and superintendents’ use of technology show comparable incongruities. While a recent descriptive study examining over 7,500 schools in Texas used a chi-square test to find positive relationship between leadership, technology use, and professional development (Mishnick, 2017), in a mixed methods study using canonical correlation analysis with 240 Texas superintendents, Plyler (2017) finds no relationship between superintendents’ technology use and district technology practices. Therefore, given the limited scope and impact that current STaR Chart research has had in examining technology leadership in schools, particularly within Texas, there is a distinct opportunity to employ more robust conceptual and empirical frameworks to fully capture the complexities of technology leadership within this unique state context.
Framework of the Study

STaR Chart Typology

Instead of providing only a narrative summary of their findings, the CEO Forum on Education and Technology (1997, 1999, 2000, 2001) outlines a typology of school types in their reports to describe subgroups of schools based on over 80,000 responses to the STaR Chart Assessment survey. Schools and districts then received a STaR Chart rating: Low Tech, Mid Tech, High Tech, and Target Tech. I will now briefly describe each of the subtypes in the typology described in the original 1997 STaR Chart Assessment report.

Low Tech schools (59%) were the highest proportion of schools profiled in the CEO Forum on Education and Technology (1997) STaR report. Low Tech schools were schools that “lack long-term technology plans” (p. 25) and that struggle to purchase technology, provide computer or Internet access, or establish network of computers for students, faculty, or staff. Approximately 26% of schools were Mid Tech schools, where “computers are ‘extras,’ used by students for isolated, fragmented activities [and] only remotely related to the curriculum” (p. 26). The report describes High Tech (12%) schools as schools with high teacher technology use and prevalent access to computers and the Internet, but few technical support staff to assist with troubleshooting and professional development. Finally, the report notes that only 3% of U.S. schools were Target Tech. The report describes Target Tech schools as schools with “technology integrators and innovators [that] have revolutionized the process of teaching and learning” (p. 28). These schools also have ubiquitous access to computers, access to many resources and content, and ongoing, collaborative professional development. Table 3-2 outlines the typology of each of the four STaR Assessment ratings, along with a description of each subgroup based on the STaR pillars and aims.
Table 3-2. Typology of Schools from the 1997 National School Technology and Readiness (STaR) Assessment (CEO Forum on Education and Technology, 1997)

<table>
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<tr>
<th>STaR Assessment School Type</th>
<th>Total Number / Percent of U.S. Schools in Sample</th>
<th>Profile Description by the “Four Pillars” (p. 14) – Hardware, Infrastructure, Digital Content, Professional Development</th>
</tr>
</thead>
</table>
| Low Tech                    | 46,799 (59%)                                  | • Hardware: Limited access to modern computers; older technology; lab environment  
                                 |                                                               | • Infrastructure: Limited Internet access; limited number of networked computers  
                                 |                                                               | • Digital Content: Limited CD-ROM resources and educational content  
                                 |                                                               | • Professional Development: Focus on technical mastery, not classroom use; limited opportunities for training |
| Mid Tech                    | 21,099 (26%)                                  | • Hardware: Moderate access to modern computers; mix of old and new technology  
                                 |                                                               | • Infrastructure: Reliable Internet access; moderate number of networked computers  
                                 |                                                               | • Digital Content: Resources are supplemented as “extras”; not used for creative work  
                                 |                                                               | • Professional Development: Limited training; no technology-related professional development |
| High Tech                   | 9,603 (12%)                                  | • Hardware: Significant access to modern computers; mostly new technology; low computer-to-student ratio  
                                 |                                                               | • Infrastructure: Prevalent Internet access; more networked computers  
                                 |                                                               | • Digital Content: Steady funding for content that is student-centered and widely available  
                                 |                                                               | • Professional Development: More professional development, but limited on-site technical support |
| Target Tech                 | 2,328 (3%)                                   | • Hardware: Ubiquitous access to modern computers; new technology; unique physical configurations of classroom computers  
                                 |                                                               | • Infrastructure: Ubiquitous Internet access; prevalent number of networked computers  
                                 |                                                               | • Digital Content: Current and relevant digital resources in the classroom and online  
                                 |                                                               | • Professional Development: On-site technical support and ongoing commitment to professional development |
Typology Subgroup Analysis

Quantitative typology subgroup analysis has emerged in the larger educational leadership (Agasisti, Bowers, & Soncin, in press; Bowers et al., 2017; Boyce & Bowers, 2016; Urick, 2016; Urick & Bowers, 2014b) and teacher technology use (Chapter 2, this volume) literature as a useful statistical method to “examine the social context of a situation using large datasets and statistical models that are designed to more thoroughly capture and summarize complex sociological systems” (Bowers et al., 2017, p. 4). Researchers use typology subgroup analysis to identify similarities and differences across a constellation of teacher and leader survey responses and generate latent groups based on these responses. There are two common typology subgroup analysis statistics, namely cluster analysis and latent class analysis (LCA). While cluster analysis methods determine latent groups based on the interpretation of the researcher or other specifications (Bowers, 2010; Goldring, Huff, May, & Camburn, 2008; Vermunt & Magidson, 2002), LCA has embedded hypothesis tests, as well as fit statistics, to empirically determine the appropriate number of latent classes (Jung & Wickrama, 2008; Masyn, 2013; Muthén & Asparouhov, 2002; Nylund, Asparouhov, & Muthén, 2007; Samuelsen & Raczynski, 2013; Vermunt & Magidson, 2002; Vermunt & Magidson, 2004). While there are several studies that use LCA to examine the extent to which there is a typology of principal perceptions of instructional leadership practices (Agasisti et al., in press; Bowers et al., 2017; Boyce & Bowers, 2016; Sebastian et al., in press; Urick & Bowers, 2014b) and teacher technology use (Chapter 2, this volume), specifying a LCA within a multilevel framework that appropriately nests teachers within schools and districts and accounts for individual and collective perspectives of leadership at all levels could provide additional insights into the extent to which the typology of STaR Chart responders interact with the school and district organizational contexts.
Multilevel Latent Class Analysis (MLCA)

Studies on technology leadership are limited in that they tend to investigate school and district technology leadership practices in isolation (McLeod & Richardson, 2011; Richardson et al., 2012; Richardson & Sterrett, 2018). Still, Richardson and Sterrett (2018) argue that there is a relationship between technology leadership at the school and district levels that researchers have yet to fully interrogate, especially as “today’s K-12 district leaders play an important role in supporting school-level leadership [and] are positioned to support and encourage teacher leadership and classroom innovation” (p. 611). Particularly within Texas, large-scale data from the STaR Charts present a unique opportunity to explore the interaction of teacher perceptions of technology leadership at the school and district levels within a single empirical model.

Quantitative studies that research the complexities of leadership practice within the context of school organizations should use statistical models that appropriately nest teachers in schools and districts (Hallinger & Heck, 2011; Hox, 2002; Raudenbush & Bryk, 2002). Multilevel statistical models are most appropriate when there is a need to control for the dependent nature of the data in order to determine the extent to which there are differences in how individuals and groups perceive leadership practices (Bellibas & Liu, 2017; Boyce & Bowers, 2018a; Hallinger & Heck, 2011; Urick & Bowers, in press). Thus, as an extension of latent class analysis (LCA), multilevel latent class analysis (MLCA) estimates the extent to which subgroups of responders on one level influence the creation and composition of respondents at a higher level (Asparouhov & Muthén, 2008; Finch & French, 2014; Henry & Muthén, 2010; Vermunt, 2003a, 2008). Within the analysis, Level 1 is typically specified as the “within-cluster” set of latent classes at the individual level, Level 2 is usually specified as a “between-cluster” set of latent classes at the organizational level, like a school or district.
& French, 2014, p. 310). MLCA modeling also allows covariates and distal outcomes at Level 1 and Level 2 with a manual three-step method (Asparouhov, 2018). Prior educational leadership studies that employ multilevel latent class analysis explore the alignment between individual and collective perceptions of instructional leadership only at the school level (Bowers et al., 2017; Urick, 2016). The goal of the present study, however, is to contribute to the current body of multilevel latent class analysis research by examining the extent to which there are different subgroups of teacher responders to the STaR Chart surveys within Texas public schools and to explore the extent to which the perceptions of technology leadership are distributed among different subgroups of Texas school districts. Given this background, the research questions for this study are:

1) To what extent are there significantly different subgroups of aggregate, school-level teacher responses to the 2011-12 Texas School Technology and Readiness (STaR) Chart surveys?

2) To what extent are school-level variables, such as urbanicity, school type, enrollment, proportion of African-American and Hispanic students, proportion of economically disadvantaged students, student-teacher ratio, and years of teacher experience, associated with group membership in the school subgroups?

3) To what extent do the mean percentage pass rates on 2012 Texas STARR/TEKS standardized tests vary across different types of schools, after controlling for covariates?

4) To what extent do the subgroups of aggregate, school-level teacher responses to the 2011-12 Texas School Technology and Readiness (STaR) Chart survey distribute across different types of districts?
5) To what extent are district-level variables, such as urbanicity, enrollment, proportion of African-American and Hispanic students, proportion of economically disadvantaged students, percent of special education students, average years of teacher experience, instructional expenditures per pupil, expenditures on instructional equipment, and expenditures on instructional staff, associated with membership in the district subgroups?

6) To what extent do the mean percentage pass rates on 2012 Texas STARR/TEKS standardized tests vary across types of districts, after controlling for covariates?

Methods

Data Sources

This study is a secondary analysis of publically available data from the Texas Education Agency (TEA) and the 2011-12 Texas School Technology and Readiness: A Teacher Tool for Planning and Self-Assessment (S TAR) surveys. Since 2006, in conjunction with Texas’s Long Range Plan for Technology 2006-2020 (Texas Education Agency, 2014), the Texas Education Agency (TEA) has mandated that Texas public school teachers complete STaR Charts in order to evaluate the progress of schools and districts in supporting improvements in technology integration. Data from the Texas STaR Charts present a unique opportunity to examine technology leadership at the school and district levels in three ways. First, in her book criticizing the accountability and standardized testing movement in U.S. schools, McNeil (2000a) mentions that it is common for other states to adopt instructional reform models that are “often justified with little more than vague claims of ‘success in Texas’” (p. xxi). However, as the second largest state in the U.S., Texas remains one of most common locales to conduct educational research in the United States because of its large student and teacher population, large variance within and between school districts, highly diverse school and district demographics, and political influence
at the federal level (Causey-Bush, 2005). From a statistical modeling standpoint, large-scale data from Texas can facilitate population-level analyses that allow for generalizable interpretations to the entire state of Texas. Second, Texas is one of the few states to still collect STaR Chart data and one of the only states to have the STaR Chart data publically accessible. Third, as deep examinations of school leadership should include teachers’ perceptions of leadership nested within an organizational context (Bowers et al., 2017; Boyce & Bowers, 2018a; Goff, Goldring, & Bickman, 2014; Hallinger & Heck, 1996, 2011; Heck & Hallinger, 2009, 2014; Leithwood & Jantzi, 2008; Urick & Bowers, 2011, 2014a), the data collection methods of the Texas STaR Chart data, along with demographic data available from the Texas Education Agency and Common Core of Data (CCD) available through the National Center for Education Statistics (NCES), offer a unique opportunity to nest data on teacher perceptions of technology leadership with multilevel analyses and include demographic variables as covariates in the model, as well as student achievement as distal outcomes.

The sample for this study focused on a subset of the full sample of public schools and districts within Texas Education Agency. For the 2011-12 academic school year, Texas Education Agency (2012a, 2012b) reported a total of 8,023 public, non-charter schools within 1,227 school districts. Although teachers were required to complete STaR Charts (Texas Education Agency, 2006, 2014), some of the aggregate school and district STaR Chart data were either incomplete or unavailable through the public data repository (Texas Education Agency, 2014). After reviewing multiple years of Texas STaR Chart data, I selected the 2011-12 school year for the analysis as it is the most complete dataset publicly available for analysis. There were a total of 7,037 schools that completed the 2011-12 STaR Charts. I then excluded Texas districts with only one school (1.4% of schools) as I wished to use multilevel modeling to nest schools in
districts, which requires more than one school per district (Shieh & Fouladi, 2003). The final sample included n= 6,935 schools (86%) across n = 910 districts (74%).

**Variables Included in the Analysis**

**Indicators.** As described in the literature review, teachers rated their perceptions of technology leadership on the STaR Chart within the four domains: (1) *Teaching and Learning (TL)*, (2) *Educator Preparation and Development (EP)*, (3) *Leadership, Administration, and Instructional Support (L)*, and (4) *Infrastructure for Technology (INT)*. Each indicator is measured on a four-point scale (1 = *Early Tech*, 2 = *Developing Tech*, 3 = *Advanced Tech*, 4 = *Target Tech*). Principals then aggregated the data from teachers, reported the mean score in each domain, and submitted a school-level summary report to the district (Texas Education Agency, 2014). Then, each district compiled each school’s overall campus report and summarizes the data from each school in a comprehensive district report. A sample of a completed school and district Texas STaR Chart with explanations of the Likert scale is located in Appendix 3-A.

I drew on the literature and theory to inform my selection of STaR Chart indicator variables in the analytic model. The covariates were selected based on school- and district-level factors that previous literature identified as moderating influences on school and district leadership and technology use in schools. I also included the 2012 aggregate standardized test scores for each school and district as distal outcomes. Under each domain, I omitted questions pertaining to online learning as recent research has argued that virtual leadership, or e-leadership, is conceptually distinct from educational technology leadership (Avolio, Kahai, & Dodge, 2000; Pei & Piaw, 2018). Responses were dichotomized into high and moderate (1 = “Advanced Tech / Target Tech”) and low to none (0 = “Developing Tech / Early Tech”). I have
outlined all of the survey questions in each domain, the corresponding response coding schema, and descriptive statistics for the variables used in the analysis in Appendix 3-B.

**Covariates.** To examine the relationship of school and district context and demographic variables to the STaR Chart responses, I merged the STaR Chart dataset with the National Center for Education Statistics Common Core of Data (2011-2012), as well as information from the TEA website for each school and district. At the school level, I included the variables of urbanicity (suburban rural, and town with urban as the reference group), school type (middle, high, and combined with elementary as the reference group), enrollment (medium, large, and extra-large with small as the reference group), proportion of African-American and Hispanic students, proportion of economically disadvantaged students, student-teacher ratio, and years of teacher experience. At the district level, I included the district-level demographic variables of urbanicity (suburban, rural, and town with urban as the reference group), enrollment (medium, large, and extra-large with small as the reference group), proportion of African-American and Hispanic students, proportion of economically disadvantaged students, percent of special education students, average years of teacher experience, instructional expenditures per pupil, expenditures on instructional equipment, and expenditures on instructional staff.

**Distal outcomes.** The 2011-12 Texas STaR Chart also did not report any student achievement outcomes for schools or districts. Consequently, I included percent pass rate on the 2012 State of Texas Assessment of Academic Readiness (STARR) and Texas Essential Knowledge and Skills (TEKS) tests in the MLCA model. TEA calculates the percent pass rate variable by aggregating test scores on end-of-course assessments in grades 3-11 and then dividing the total number of grade tests that met the Phase-In Level II or above passing standard on the STARR or TEKS (Texas Education Agency, 2013) by the total number of students who
completed the STAAR or TEKS assessments in 2012. I included the percent pass rate for each school as distal outcomes on Level 1, as well as the percent pass rate for the district as distal outcomes at Level 2 of the MLCA model.

**Missing variables.** There were neither missing data in the school or district indicators variables and covariates nor in the district-level distal outcomes. There were missing data for the school level distal outcomes with approximately 7% of schools missing data on the percentage pass rate for the 2012 STARR mathematics scores and approximately 6% of schools missing data on the percentage pass rate for the 2012 STARR reading scores. I performed listwise deletion of the missing cases during the last step in calculating the distal outcomes.

Survey questions, variable recodes, and descriptive statistics for the school-level covariates and distal outcomes are in Appendix 3-C. Survey questions, variable recodes, and descriptive statistics for the district-level covariates and distal outcomes are in Appendix 3-D.

**Analytic Model**

To examine the extent to which there is a typology of responders to the school and district STAAR Charts, nesting schools within districts, I used a nonparametric, multilevel latent class analysis (LCA) framework in the present study (Asparouhov & Muthén, 2008; Collins & Lanza, 2010; Finch & French, 2014; Henry & Muthén, 2010; Vermunt, 2003a, 2008). In a general sense, latent class analysis (LCA) is a type of mixture modeling approach that uses hypothesis tests to determine the extent to which there are different subtypes of respondents across survey responses (Jung & Wickrama, 2008; Magidson & Vermunt, 2004; Masyn, 2013; Múthen, 2004; Muthén & Asparouhov, 2002; Samuelsen & Raczynski, 2013; Vermunt & Magidson, 2002; Vermunt & Magidson, 2004). Furthermore, because of the nested structure of the STAAR Chart data, I decided to use a two-level LCA framework to estimate latent classes at
Level 1 and then determine the extent to which the subgroups at Level 1 cluster across the different latent classes at Level 2 (Asparouhov & Muthén, 2008; Finch & French, 2014; Henry & Muthén, 2010; Vermunt, 2003a, 2008). I include the statistical equation for the MLCA in Equation 3-1.


\[
P(C_{ij} = t | CB_j = m) = \frac{\exp(\gamma_{tm})}{\sum_{r=1}^{p} \exp(\gamma_{rm})}
\]

In which:
- \(c\) = classes in latent class model
- \(i\) = individual responses to \(m\) items
- \(j\) = value of level 2 group membership
- \(t\) = number of Level 1 latent classes
- \(CB_j\) = group \(j\) score on latent class variable
- \(\gamma\) = latent class membership probabilities
- \(m\) = categorical items

I conducted the primary data analysis in \textit{MPlus 7.11} (Muthén & Muthén, 2012) following the recommendations from the LCA methods literature. I began the analysis by conducting a three-step LCA on the school-level \textit{STaR Chart} data to estimate the correct number of classes at Level 1 as recommended in the literature (Bowers et al., 2017; Henry & Muthén, 2010). In the first step, I adapted the \textit{MPlus} syntax from a prior LCA study (Chapter 2, this volume) and performed an initial LCA that only included indicator variables in the model. This initial, unconditional model is important to ensure that other variables do not bias the enumeration of the latent groups in the first step of the model (Asparouhov & Muthén, 2013; Jung & Wickrama, 2008; Masyn, 2013). Next, the LCA literature outlines an iterative approach to determine the appropriate number of classes and to assess model fit (Jung & Wickrama, 2008; Nylund et al., 2007; Nylund-Gibson, Grimm, Quirk, & Furlong, 2014). As recommended in the literature, there
are two different methods and statistics to consider when assessing model fit, the Bayesian information criteria (BIC) (Magidson & Vermunt, 2004; Muthén & Asparouhov, 2002; Nylund et al., 2007) and the Lo-Mendell-Rubin (LMR) adjusted likelihood test (Lo, 2005; Lo, Mendell, & Rubin, 2001). Beginning with the two-class model, I specified the first model, $k$, and iteratively increased the number of classes to compare model fit between the models, comparing whether the specified model has a larger BIC value than the $k-1$ model (Magidson & Vermunt, 2004; Muthén & Asparouhov, 2002; Nylund et al., 2007) and whether the p-value from the hypothesis test in the LMR test is no longer significant (Lo, 2005; Lo et al., 2001). When the BIC of the current model is lower than the previous model and the hypothesis test p-value of the LMR test is no longer significant, the previous model is the best fit. I used the BIC and the LMR tests as they are the more conservative estimates of model fit (Jung & Wickrama, 2008; Nylund et al., 2007; Nylund-Gibson et al., 2014). After analyzing the school-level data, I repeated the exact process outlined above with the district-level STaR Chart data to estimate the appropriate number of classes at Level 2 (Bowers et al., 2017; Henry & Muthén, 2010).

After identifying the number of latent classes at the school (Level 1) and district (Level 2) levels, I then merged the school and district level STaR Chart data into one dataset and adapted the MPlus code provided in the Bowers et al. (2017) multilevel LCA study to test a two-level LCA model that nests the Level 1 data in the Level 2 data in order to determine the extent to which the school-level subgroups distribute across different types of district-level subgroups. The two-level model also included a cross-level interaction where school-level subgroups (Level 1) were the indicator variables for the LCA at the district-level (Level 2), allowing the subgroups at Level 1 to influence the creation of subgroups at Level 2 (Bowers et al., 2017; Henry & Muthén, 2010). To avoid issues of power and Type I errors common in local fit statistics in
MLCA (Nagelkerke, Oberski, & Vermunt, 2017) and following the recommendations in the literature (Bowers et al., 2017; Henry & Muthén, 2010; Urick, 2016), I relied on fit statistics from the individual school-level LCA and district-level LCA to determine the number of appropriate classes to specify in the multilevel model. I also examined the log likelihood values to ensure that the model replicated multiple times at the global minima value that provides evidence of best model fit for the data (Asparouhov & Muthén, 2008; Finch & French, 2014; Jung & Wickrama, 2008; Vermunt, 2003a, 2008). Because there is not a single auxiliary command available in *MPlus* to conduct a three-step multilevel LCA that estimates covariates and distal outcomes in an omnibus model (Asparouhov, 2018), based on recommendations from the *MPlus* guide (Muthén & Muthén, 2012), I manually added the school-level and district covariates under the WITHIN and BETWEEN command to trigger the program to conduct a *post hoc* logistic regression with the covariates on the school and district levels. The *MPlus* code for the MLCA model is included in Appendix 3-E.

Finally, as recommended in the LCA literature (Agasisti et al., in press), I conducted two *post hoc* ANCOVAs on the distal outcomes to determine the extent to which there are statistically significant mean differences on the 2012 Texas standardized end-of-course assessments among the subgroups at the school and district levels, controlling for the covariates. The SPSS syntax for the ANCOVA is included in Appendix 3-F. I included the school or district subgroups as the independent variables and school or district percent pass rate on the 2012 Texas standardized end-of-course assessments as the dependent variables. I also controlled for all of the covariates listed in the previous section in each of the models I tested. Finally, in order to estimate a magnitude of the independent effect of the subgroups on the percent pass rates, I also calculated eta squared as an estimate of the total variance of the dependent variable that can be
explained by the independent variable (Mertler & Vannatta Reinhart, 2017). Before conducting the analysis, I verified the statistical assumptions of analyses of covariance as outlined in the literature (Mertler & Vannatta Reinhart, 2017), including testing the distal outcome variables for independence, normality, linearity, homogeneity of regression, and equal variances. My model violated the homogeneity of regression and equal variance assumptions, which I will discuss further in the limitations section.

As will be presented below in the results, I tested a two-level model that contained three subgroups at the school-level and four subgroups at the district level. As standard in these types of analyses (Bowers et al., 2017; Henry & Muthén, 2010; Urick, 2016), Figure 3-1 is the structural and conceptual model I tested for the study. The two-level latent class analysis contains a school-level (Level 1) LCA model that tests the extent to which there are three different latent class subgroups (“Latent Classes CW”) using the different indicator variables within the four STaR Chart domains described above: Teaching and Learning (TL), Educator Preparation and Development (EP), Leadership, Administration, and Instructional Support (L), and Infrastructure for Technology (INT). The Level 1 model also includes eight school-level covariates that predict membership in the school-level subgroups, and the two school-level distal outcomes, percent proficient on the 2012 Texas STARR/TEKS tests. Additionally, Figure 3-1 also shows how the three school-level (“CW”) latent classes interact with another LCA at the district-level that tests the extent to which the school-level (Level 1) subgroups distribute across four district-level subgroups (“Latent Classes CB”). At Level 2, I also include the ten district-level covariates and the two district-level distal outcomes, percent pass rate on the 2012 Texas STARR/TEKS standardized tests.
Figure 3-1. Structural and Conceptual Equation Model for Multilevel Latent Class Analysis of Texas School Technology and Readiness (STaR) Charts

Structural and Conceptual Equation Model of Multilevel Latent Class Analysis (MLCA) of Texas STaR Charts with three classes at Level 1 school level (CW) and four classes at Level 2 district level (CB). The subgroups of school-level responses are estimated at Level 1 according to the responses across four domains on the STaR Charts. Covariates predict subgroups of school-level subgroups. Distal outcomes include school-level achievement data from the 2012 State of Texas Assessments of Academic Readiness (STARR) tests. At Level 2, the means in the CW classes are allowed to vary across Level 2. Covariates predict subgroups of district-level subgroups. Distal outcomes include district-level achievement data from the 2012 State of Texas Assessments of Academic Readiness (STARR) tests.
Results

The purpose of this study is to describe school and district leadership from a new conceptual and empirical lens by examining the extent to which there are different types of school and district perceptions of technology leadership using the 2011-12 Texas School Technology and Readiness (STaR) Charts. In this results section, I first present the results of the study by describing the fit of the multilevel latent class analysis model. Next, I describe the three different subgroups of schools and the four different subgroups of districts, as defined by their responses to the STaR Chart survey. Third, I describe the results of how each of the three different types of schools distribute across each of the four different types of districts. Fourth, I interpret the means and odds table for the covariates at the school- and district-levels. Finally, I present the findings of the analysis of the distal outcomes and then turn to a discussion of the findings.

Model Fit for the Multilevel Latent Class Analysis (MLCA)

As described in the methods, I followed the recommendations of the literature on iteratively fitting a two-level latent class analysis (MLCA) model by first estimating the model fit at Level 1 (schools) and Level 2 (districts) to enumerate the correct number of latent classes at each level first (Asparouhov & Muthén, 2008; Bowers et al., 2017; Henry & Muthén, 2010; Vermunt, 2003b, 2016), and then continuing to the full two-level model. For the level 1 school-level LCA model, the three class model fit the data well with the lowest BIC and a significant LMR test ($p < 0.001$) and an entropy of 0.857. For the level 2 district-level LCA model, the four class model fit the data well with the lowest BIC and a significant LMR test ($p < 0.001$) and an entropy of 0.849. Next, I fit the full two-level latent class analysis model with three classes at Level 1 (school level) and four classes at Level 2 (district level) with a cross-level interaction
between both levels, as the district-level model is identified through the ratios of the three
different school-level subgroup schools due to the inclusion of the cross-level interaction (see
methods section). The model fit the data well with fit statistics of $\text{AIC} = 123168.479$, $\text{BIC} = 124126.686$, $-\text{Log likelihood} = 61444.239$, and entropy $= 0.813$. As additional evidence of model
fit, the classification probabilities table indicates a high probability of a school belonging to a
particular class being placed in the correct class when fitting the model (Bowers et al., 2017;
Nylund et al., 2007; Urick, 2016). The classification probabilities indicate that the multilevel
model fit the data well as the probabilities in the diagonal cells are larger than 0.7 and the
probabilities in the off-diagonal cells are less than 0.3. Appendix 3-G contains the classification
probabilities for latent class membership for the multilevel model.

At Level 1 (school level), the MLCA model identified three different groups of Texas
schools as identified by the aggregate teacher responses to the 2011-12 STaR Chart surveys. The
final school-level model was an ordinal model with $\text{High STaR Schools (29.4\%)}, \text{Moderate STaR Schools (42.3\%)}, \text{and Low STaR Schools (28.2\%)}. \text{At Level 2 (district level), the MLCA model identified four different subgroups of Texas district respondents to the 2011-12 STaR Chart surveys: Model STaR Districts (19.8\%), High STaR Districts (22.8\%), Moderate STaR Districts (42.3\%), and Low STaR Districts (22.6\%).}
Figure 3-2. Statistical Indicator Plot for Multilevel Latent Class Analysis Results for School-Level Indicators (Level 1) within the *Model STaR Districts* Subgroup (Level 2)

Statistical indicator plot for multilevel latent class analysis (LCA) results showing three subgroups of school-level responders (Level 1) in one subgroup at Level 2 (district-level). Moderate *STaR* schools (42.3%), the largest school subgroup, have high patterns of technology usage and leadership collaboration with low teacher technology professional development participation, while High *STaR* schools (29.4%) report the highest mean responses across all the *STaR* Chart indicators. Low *STaR* schools (28.2%) are the smallest subgroup and also have the lowest mean response across all of the *STaR* indicators. One indicator, Internet access connectivity, is consistently high across all subgroups at the school- and district-levels.

Three subgroup responses across all district subgroups are similar to the statistical indicator plot above. Appendix 3-H provides a comparison of the three school subgroups (Level 1) responses across all four district subgroups (Level 2).
The responses of the three school subgroups at Level 1 are an ordinal outcome of Low, Moderate, and High STaR schools. The High STaR Schools subgroup made up 29.4% of the schools. This subgroup of schools is typified by the highest use of technology in classrooms (88.0%), highest ability to connect technology to content areas (98.9%), highest use of digital content in instruction (98.9%), highest perceptions of effective leadership and vision (98.4%), as well as high amounts of classroom technology (95.1%) and adequate technology budgets (94.2%). In comparison to the other subgroups, the high amount and quality of professional development experiences typify the High STaR Schools subgroup with respondents noting the high availability of professional development experiences (95.5%) and the levels of understanding to use technology to teach higher order thinking and customized learning environments (96.1%). High STaR Schools also have the highest amount of hours of professional development participation (50.2%) within the three school typology. Teachers in the High STaR Schools subgroup report that their schools have strong technology plans (92.3%), highest student mastery of the technology applications standards (74.3%), unanimous positive perceptions of using technology to communicate with the community (100%), and high teacher-led instructional support for technology integration (86.9%), all of which distinguishes this group from the other two subgroups.

In contrast, the Low STaR Schools subgroup, which makes up 28.2% of the schools, has the lowest mean response pattern across all of the indicators. The STaR Chart survey indicators that typify the Low STaR Schools subtype are little to no teacher (3.9%) and student mastery (0.0%) of the Texas technology standards, low levels of classroom technology use (3.9%), and no opportunities for professional development (0.0%). Teachers in the Low STaR Schools subgroup also reported very few technology goals in their campus technology plans (3.6%) and
limited instructional support for technology (3.9%). In terms of infrastructure, schools in the Low STaR Schools subgroup also have the lowest mean survey response for student access to computers (3.9%), amount of available classroom technology (19.2%), and low technology budgets (11.5%). Despite the Low STaR Schools subtype having the lowest response rate across all of the indicators, the proportion of survey responses related to using technology to communicate with parents and the larger community (62.5%), as well as Internet access (80.7%) are much more closely aligned to the other subgroup responses.

The Moderate STaR Schools subgroup is the largest subgroup at 42.3% of the schools. The Moderate STaR Schools subgroup share some characteristics related to the High STaR Schools subgroup in that they have a high frequency of technology-infused instructional content (87.9%) and digital resources that are connected to a content area (77.8%). Like the High STaR Schools subtype, the Moderate STaR Schools subgroup also report moderate levels of understanding from teachers in how to integrate technology (69.5%), strong leadership vision for technology (78.8%), and strong use of technology to communicate with the school community (95.6%). However, the Moderate STaR Schools subgroup also shares several characteristics with the Low STaR Schools subgroup. Respondents in the Moderate STaR Schools subgroup report moderate patterns of technology use in the classroom (40.9%), moderate student (32.7%) and teacher mastery (23.8%) of the technology applications standards, moderate perceptions in the capability of educators to integrate technology in classroom (29.2%), moderate participation in technology professional development (20.9%), and low instructional support for technology integration (35.2%). In terms of infrastructure, the Moderate STaR Schools subgroup also report a moderate amount students per classroom computers (32.7%), but higher shared access to technology (65.4%) and strong Internet connectivity (99.7%).
Using these three different school-level subgroups in the MLCA model to identify different district subgroups by the ratios of these school subgroups, I turn next to describing the four district-level subgroups from the MLCA model. Figure 3-3 provides the total number (Panel A) and percent proportion (Panel B) of school subgroups within the four district subgroups. Given these different proportions of the three school subgroups across the STaR Chart responses, I named the four district subgroups as *Model STaR Districts* (19.8%), *High STaR Districts* (22.8%), *Moderate STaR Districts* (34.6%), and *Low STaR Districts* (22.6%). As detailed in the stacked column graph in Figure 3-3, Panel A shows the total number of schools across each of the district subgroups. I also color coded the proportion of each of the three school-level subgroups within each district subgroup, with the *Low STaR Schools* subgroup in light gray, the *Moderate STaR Schools* subgroup in dark gray, and the *High STaR Schools* subgroup in black. Panel B in Figure 3-4 shows the same data as in the first panel, but as a percentage of school subgroups across the district subgroups.
Figure 3-3. Total Sample and Percent Proportion of Level 1 (Schools) Subgroups Across Level 2 (District) Subgroups

Panel A:

Total School Sample of Level 1 (School) Subgroups Across Level 2 (District) Subgroups

Panel B:

Total Percent Proportions of Level 1 (School) Subgroups Across Level 2 (District) Subgroups
As demonstrated in Figure 3-3, there are stark differences in the proportions of the three school-level subgroups within the four district-level subgroups. The *Low STaR Districts* subgroup (Figure 3-3, far left), 22.6% of districts in Texas, has the largest proportion of *Low STaR Schools* (62.1%), as well as lowest proportion of *Moderate STaR Schools* (31.9%) and *High STaR Schools* (5.9%) in all of the four district subgroups.

The *Moderate STaR Districts* subgroup (Figure 3-3, middle left) is the largest district-level subgroup (34.6%) and is comprised of 50.1% of schools from the *Moderate STaR Schools* subgroup and 33.2% of schools from the *Low STaR Schools* group, the second largest proportion. The *Moderate STaR Districts* subgroup also has 16.6% of schools from the *High STaR Schools* subtype. Whereas, the *High STaR Districts* subgroup (Figure 3-3, middle right) has the highest proportion of *Moderate STaR Schools* (57.4%) and the second highest proportion of *High STaR Schools* (32.4%). 161 schools (10.1%) in the *Low STaR Schools* subtype were classified in the *High STaR Districts* subgroup.

Finally, the *Model STaR Districts* subgroup (Figure 3-3, far right) represents the smallest proportion of schools overall and district (19.8%). The *Model STaR Districts* were typified by the highest proportion of *High STaR Schools* subgroup respondents (75.2%) across all of the district-level subtypes and the lowest proportion of schools from the *Moderate STaR Schools* (22.9%) and the *Low STaR Schools* (1.8%) subgroups. As an example of the sharp contrast between the district types, only 26 schools (1.8%) belonging to the *Low STaR Schools* subgroup were placed in the *Model STaR Districts* subtype, whereas almost two-thirds of Texas schools in the *Low STaR Schools* subgroup (62.1%) were placed in the *Low STaR Districts* subtype. However, it is important to note that across all four district subgroups, each subgroup contained some proportion of the three school-level subgroups.
MLCA Model Covariates for Community, Demographic, and Context Effects

Having described the different school and district response subgroups, I now turn to providing the estimates of the covariates at the school (Level 1) and district (Level 2) level, as it is important to understand which school and district community, demographic, and context variables are related to the probability of a school or district being in each of the subgroups at level 1 or level 2. I used the High STaR Schools subgroup at Level 1 and the Low STaR Districts subgroup at Level 2 as the reference groups to aid with interpretation. Table 3-3 is a summary of the means and odds ratios table of the covariates associated with the three school-level subgroups, while Table 3-3 is a summary of the means and odds ratio table of the covariates associated with the four district-level subgroups.
Table 3-3. Means and Odds Ratios for Level 1 (School Level) Covariates with *High STaR Schools* Subgroup as the Reference Group

<table>
<thead>
<tr>
<th>Variable</th>
<th>CW3 High STaR Schools (29.4%)</th>
<th></th>
<th>CW1 Low STaR Schools (28.2%)</th>
<th></th>
<th>CW2 Mod STaR Schools (42.3%)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Odds Ratio</td>
<td>Mean</td>
<td>Odds Ratio</td>
<td>Mean</td>
<td>Odds Ratio</td>
</tr>
<tr>
<td>Urbanicity:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Suburban</td>
<td>0.24</td>
<td>—</td>
<td>0.14</td>
<td>—</td>
<td>0.32</td>
<td>—</td>
</tr>
<tr>
<td>Town</td>
<td>0.12</td>
<td>—</td>
<td>0.14</td>
<td>—</td>
<td>0.32</td>
<td>—</td>
</tr>
<tr>
<td>Rural</td>
<td>0.33</td>
<td>—</td>
<td>0.32</td>
<td>—</td>
<td>0.32</td>
<td>—</td>
</tr>
<tr>
<td>School type:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle</td>
<td>0.20</td>
<td>—</td>
<td>0.24</td>
<td>1.39**</td>
<td>0.21</td>
<td>0.16</td>
</tr>
<tr>
<td>High</td>
<td>0.19</td>
<td>—</td>
<td>0.16</td>
<td>0.56***</td>
<td>&lt;0.001</td>
<td>0.17</td>
</tr>
<tr>
<td>Combined</td>
<td>0.04</td>
<td>—</td>
<td>0.06</td>
<td>—</td>
<td>0.04</td>
<td>—</td>
</tr>
<tr>
<td>Enrollment:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>0.41</td>
<td>—</td>
<td>0.36</td>
<td>—</td>
<td>0.39</td>
<td>—</td>
</tr>
<tr>
<td>Large</td>
<td>0.03</td>
<td>—</td>
<td>0.04</td>
<td>1.95**</td>
<td>0.021</td>
<td>0.03</td>
</tr>
<tr>
<td>Extra large</td>
<td>0.05</td>
<td>—</td>
<td>0.03</td>
<td>2.40***</td>
<td>0.001</td>
<td>0.05</td>
</tr>
<tr>
<td>% African-American students</td>
<td>10.29</td>
<td>—</td>
<td>12.58</td>
<td>—</td>
<td>12.23</td>
<td>—</td>
</tr>
<tr>
<td>% Hispanic students</td>
<td>43.25</td>
<td>—</td>
<td>55.12</td>
<td>—</td>
<td>49.17</td>
<td>—</td>
</tr>
<tr>
<td>% Special education students</td>
<td>8.84</td>
<td>—</td>
<td>9.70</td>
<td>1.04*</td>
<td>0.016</td>
<td>9.70</td>
</tr>
<tr>
<td>% Economically disadvantaged</td>
<td>54.55</td>
<td>—</td>
<td>70.17</td>
<td>1.02**</td>
<td>0.003</td>
<td>70.17</td>
</tr>
<tr>
<td>Student-teacher ratio</td>
<td>14.93</td>
<td>—</td>
<td>14.75</td>
<td>0.96*</td>
<td>0.031</td>
<td>14.75</td>
</tr>
<tr>
<td>Average teacher experience</td>
<td>12.12</td>
<td>—</td>
<td>11.95</td>
<td>—</td>
<td>12.02</td>
<td>—</td>
</tr>
</tbody>
</table>

Note: *p < .10; *p ≤ .05; **p ≤ .01; ***p ≤ .001, two-tailed
Table 3-3 provides the school-level covariates for the MLCA at Level 1 of the model. Schools from town and rural urbanicity contexts are 1.44 ($p = 0.037$) and 1.40 ($p = 0.011$) times more likely to be in the Moderate STaR Schools than the High STaR Schools subgroup in comparison to the urban reference group. When considering school level of elementary, middle or high school, middle schools are 1.39 times ($p = 0.010$) more likely to be in the Moderate STaR Schools than the High STaR Schools subgroup in comparison to the elementary school reference group. In contrast, high schools are less likely to be Moderate or Low STaR Schools. As odds ratios below 1.0 are difficult to interpret, I invert each odds ratio that is less than 1.0. In Table 3-3, high schools are 1.78 times (1/0.56) less likely ($p < 0.001$) and 1.61 times (1/0.62) less likely ($p = 0.001$) to be Moderate or Low STaR Schools in comparison to elementary schools.

Pertaining to school enrollment, large schools (1,201 – 1,800 students) and extra-large schools (more than 1,801 students) are 1.95 times ($p = 0.021$) and 2.4 times ($p < 0.001$) more likely to be in the Low STaR Schools subgroup in comparison to the small schools (1 – 499 students) reference group. Extra-large schools are also 1.73 times ($p = 0.010$) more likely to be in the Moderate STaR Schools subgroup than the High STaR Schools subtype. Also, as student-teacher ratio increases, schools are 1.04 times less likely to be in the Low STaR Schools subgroup than in the High STaR Schools subgroup. Specific demographic contexts are also associated with membership in the school-level subgroups. Schools with higher proportions of special education students are 1.04 times ($p = 0.016$) more likely to be in the Low STaR Schools subgroup. Likewise, schools with higher proportions of economically disadvantaged students are 1.02 times ($p = 0.003$) more likely to in the Low STaR Schools subgroup as well. I will now present means and odds ratio table for the four district subgroups.
Table 3-4. Means and Odds Ratios for Level 2 (District-Level) Covariates with Low STaR Districts Subgroup as the Reference Group

<table>
<thead>
<tr>
<th>Variable</th>
<th>CB4 Low STaR Districts (22.8%)</th>
<th>CB1 High STaR Districts (22.7%)</th>
<th>CB2 Moderate STaR Districts (34.6%)</th>
<th>CB3 Model STaR Districts (19.8%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Odds Ratio</td>
<td>Mean</td>
<td>Odds Ratio</td>
</tr>
<tr>
<td>Urbanicity:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Suburban</td>
<td>0.28</td>
<td>0.36</td>
<td>0.56</td>
<td>0.23</td>
</tr>
<tr>
<td>Town</td>
<td>0.17</td>
<td>0.28</td>
<td>0.17</td>
<td>0.22</td>
</tr>
<tr>
<td>Rural</td>
<td>0.18</td>
<td>0.13</td>
<td>0.07</td>
<td>0.16</td>
</tr>
<tr>
<td>Enrollment:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>0.15</td>
<td>0.13</td>
<td>0.00</td>
<td>0.03</td>
</tr>
<tr>
<td>Large</td>
<td>0.22</td>
<td>0.27 10.49*</td>
<td>0.027</td>
<td>0.19</td>
</tr>
<tr>
<td>Extra large</td>
<td>0.41</td>
<td>0.58</td>
<td>0.77</td>
<td>0.51</td>
</tr>
<tr>
<td>% African-American students</td>
<td>13.60</td>
<td>12.74</td>
<td>11.27</td>
<td>0.92* 0.013</td>
</tr>
<tr>
<td>% Hispanic students</td>
<td>49.49</td>
<td>42.10</td>
<td>59.80</td>
<td>36.50 0.96* 0.010</td>
</tr>
<tr>
<td>% Economically disadvantaged</td>
<td>65.54</td>
<td>53.90</td>
<td>69.69</td>
<td>48.22</td>
</tr>
<tr>
<td>% Special education students</td>
<td>8.98</td>
<td>9.43</td>
<td>8.44</td>
<td>9.00</td>
</tr>
<tr>
<td>Average teacher experience</td>
<td>12.03</td>
<td>12.14</td>
<td>11.88</td>
<td>12.16</td>
</tr>
<tr>
<td>District expenditures -</td>
<td>5.02</td>
<td>4.96</td>
<td>5.34</td>
<td>5.33</td>
</tr>
<tr>
<td>instruction per pupil</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(by thousands)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expenditures - instructional</td>
<td>4.63</td>
<td>5.14</td>
<td>5.32</td>
<td>4.27</td>
</tr>
<tr>
<td>equipment (log10 transformed)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>District expenditures -</td>
<td>6.34</td>
<td>6.67</td>
<td>6.83</td>
<td>6.38</td>
</tr>
<tr>
<td>instructional staff</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(log10 transformed)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: ~p < .10; *p ≤ .05; **p ≤ .01; ***p ≤ .001, two-tailed
Table 3-4 contains the district-level covariates for the MLCA at Level 2 of the model. Large school districts (2,400 – 9,999 students) are 10.49 times (p = 0.027) more likely to be in the High STaR Districts subgroup than in the Low STaR Districts subtype in comparison to small school districts (1 – 1,299 students). Students’ racial background is also associated with membership in the district subgroups. After inverting the odds ratios that are less that are less than 1.0, results show that African-American students are 1.08 times (1/0.92) less likely to be in either the Moderate (p = 0.013) or Model STaR Districts (p = 0.004) subgroups than in the Low STaR Districts subgroup. Similarly, Hispanic students are 1.04 times (1/0.96) less likely to be in the Model STaR Districts subtype than in the Low STaR Districts subtype.

**Distal Outcomes for Texas STAAR and TEKS Standardized Test Scores**

Finally, I describe the results of the stepwise ANCOVA that examines the extent to which there are significant differences across the mean percentage of student proficiency on the 2012 State of Texas Assessment of Academic Readiness (STARR) and Texas Essential Knowledge and Skills (TEKS) assessments across the school and district-level subgroups, controlling for the covariates. Again, I used the High STaR Schools subgroup at Level 1 and the Low STaR Districts subgroup at Level 2 as the reference groups to aid with interpretation. Table 3-5 is a summary of the analysis of covariance for the distal outcomes at Level 1 (school-level). I also include a summary of adjusted group means p-values associated with the three school subgroups after controlling for the covariates and testing for the independent effect of the school subgroups in Table 3-6. I then present Table 3-7 as the summary of the analysis of covariance for the distal outcomes at Level 2 (district-level) and include a summary of adjusted group means and p-values associated with the four district-level subgroups after controlling for the covariates and testing for the independent effect of the district subgroups in Table 3-8.
Table 3-5. Summary of Analysis of Covariance Results for MLCA Level 1 (School-Level) Subgroups and Covariates

<table>
<thead>
<tr>
<th>Variable</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>F</th>
<th>p</th>
<th>$\eta^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between treatments</td>
<td>530435.75</td>
<td>17</td>
<td>31202.103</td>
<td>492.480</td>
<td>&lt;0.001</td>
<td>0.563</td>
</tr>
<tr>
<td><strong>Urbanicity:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Suburban</td>
<td>1633.135</td>
<td>1</td>
<td>1633.135</td>
<td>25.777</td>
<td>&lt;0.001</td>
<td>0.004</td>
</tr>
<tr>
<td>Town</td>
<td>1800.267</td>
<td>1</td>
<td>1800.267</td>
<td>28.415</td>
<td>&lt;0.001</td>
<td>0.004</td>
</tr>
<tr>
<td>Rural</td>
<td>660.608</td>
<td>1</td>
<td>660.608</td>
<td>10.427</td>
<td>0.001</td>
<td>0.002</td>
</tr>
<tr>
<td><strong>School type:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle</td>
<td>3525.183</td>
<td>1</td>
<td>3525.183</td>
<td>55.640</td>
<td>&lt;0.001</td>
<td>0.009</td>
</tr>
<tr>
<td>High</td>
<td>8459.585</td>
<td>1</td>
<td>8459.585</td>
<td>133.522</td>
<td>&lt;0.001</td>
<td>0.020</td>
</tr>
<tr>
<td>Combined</td>
<td>9.613</td>
<td>1</td>
<td>9.613</td>
<td>0.152</td>
<td>0.697</td>
<td>0.000</td>
</tr>
<tr>
<td><strong>Enrollment:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>376.528</td>
<td>1</td>
<td>376.528</td>
<td>5.943</td>
<td>0.015</td>
<td>0.001</td>
</tr>
<tr>
<td>Large</td>
<td>756.160</td>
<td>1</td>
<td>756.160</td>
<td>11.935</td>
<td>0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>Extra-large</td>
<td>790.008</td>
<td>1</td>
<td>790.008</td>
<td>12.469</td>
<td>&lt;0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>% African-American students</td>
<td>9400.959</td>
<td>1</td>
<td>9400.959</td>
<td>148.380</td>
<td>&lt;0.001</td>
<td>0.022</td>
</tr>
<tr>
<td>% Hispanic students</td>
<td>819.607</td>
<td>1</td>
<td>819.607</td>
<td>12.936</td>
<td>&lt;0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>% Special education students</td>
<td>3744.208</td>
<td>1</td>
<td>3744.208</td>
<td>59.097</td>
<td>&lt;0.001</td>
<td>0.009</td>
</tr>
<tr>
<td>% Economically disadvantaged</td>
<td>95350.859</td>
<td>1</td>
<td>95350.859</td>
<td>1504.974</td>
<td>&lt;0.001</td>
<td>0.188</td>
</tr>
<tr>
<td>Student-teacher ratio</td>
<td>837.548</td>
<td>1</td>
<td>837.548</td>
<td>13.219</td>
<td>&lt;0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>Average teacher experience</td>
<td>1330.074</td>
<td>1</td>
<td>1330.074</td>
<td>20.993</td>
<td>&lt;0.001</td>
<td>0.003</td>
</tr>
<tr>
<td>Level 1 (school) subgroups</td>
<td>8550.638</td>
<td>2</td>
<td>4275.319</td>
<td>67.480</td>
<td>&lt;0.001</td>
<td>0.020</td>
</tr>
<tr>
<td>Error</td>
<td>411061.236</td>
<td>6488</td>
<td>63.357</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>37688051.000</td>
<td>6506</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3-6. Adjusted Means and P-Values for Level 1 (School-Level) Distal Outcomes

<table>
<thead>
<tr>
<th>Variable</th>
<th>CW3 High STaR Schools (29.4%)</th>
<th>CW1 Low STaR Schools (28.2%)</th>
<th>CW2 Moderate STaR Schools (42.3%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adjusted Mean</td>
<td>p</td>
<td>Adjusted Mean</td>
</tr>
<tr>
<td>% STARR/TEKS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2012 All Subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pass</td>
<td>76.57</td>
<td>&lt;0.001</td>
<td>73.44***</td>
</tr>
</tbody>
</table>

Note: ~p < .10; *p ≤ .05; **p ≤ .01; ***p ≤ .001
Table 3-5 describes the ANCOVA results for the school level distal outcomes, controlling for the covariates, for the MLCA at Level 1 of the model. Results indicate a small, statistically significant main effect for the Level 1 school subgroups \([F(1, 6488) = 64.48, p < 0.001, \text{partial } \eta^2 = 0.020]\) on the school percent proficient on the 2012 Texas STARR/TEKS achievement tests. The majority of the covariates, excluding combined schools, significantly influenced the dependent variable of the school-level pass rates on the 2012 Texas STARR/TEKS achievement tests as well. In comparing the effect sizes of all of the covariates with Cohen’s guidelines (0.2 – small effect, 0.5 – moderate effect, 0.8 – large effect), the covariate of the total proportion of economically disadvantaged students had a small, but overall, the largest, effect size among all of the covariates \([F(1, 6488) = 1504.974, p < 0.001, \text{partial } \eta^2 = 0.188]\). Additionally, Table 3-6 presents the adjusted means for the school percent proficient on the 2012 Texas STARR/TEKS achievement tests, which indicate that the High STaR Schools subtype \((M = 76.57)\) have significantly higher in standardized test score pass rates on the 2012 Texas STARR/TEKS assessment than the Moderate \((M = 75.28)\) or Low STaR Schools \((M = 75.28)\) subgroups, when controlling for the covariates. Finally, I describe the ANCOVA results in Table 3-7 and adjusted means for the district level (Level 2) distal outcomes in Table 3-8.
### Table 3-7. Summary of Analysis of Covariance Results for MLCA Level 2 (District-Level) Subgroups and Covariates

<table>
<thead>
<tr>
<th>Variable</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>F</th>
<th>p</th>
<th>( \eta^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between treatments</td>
<td>337494.773</td>
<td>17</td>
<td>19852.634</td>
<td>1326.687</td>
<td>&lt;0.001</td>
<td>0.765</td>
</tr>
<tr>
<td><strong>Urbanity:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>City</td>
<td>464.882</td>
<td>1</td>
<td>464.882</td>
<td>31.067</td>
<td>&lt;0.001</td>
<td>0.004</td>
</tr>
<tr>
<td>Suburban</td>
<td>728.996</td>
<td>1</td>
<td>728.996</td>
<td>48.716</td>
<td>&lt;0.001</td>
<td>0.007</td>
</tr>
<tr>
<td>Town</td>
<td>264.685</td>
<td>1</td>
<td>264.685</td>
<td>17.688</td>
<td>&lt;0.001</td>
<td>0.003</td>
</tr>
<tr>
<td><strong>Enrollment:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>415.809</td>
<td>1</td>
<td>415.809</td>
<td>27.787</td>
<td>&lt;0.001</td>
<td>0.004</td>
</tr>
<tr>
<td>Large</td>
<td>210.010</td>
<td>1</td>
<td>210.010</td>
<td>14.034</td>
<td>&lt;0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>Extra-large</td>
<td>26.290</td>
<td>1</td>
<td>26.290</td>
<td>1.757</td>
<td>0.185</td>
<td>0.000</td>
</tr>
<tr>
<td>% African-American students</td>
<td>1337.457</td>
<td>1</td>
<td>1337.457</td>
<td>89.378</td>
<td>&lt;0.001</td>
<td>0.013</td>
</tr>
<tr>
<td>% Hispanic students</td>
<td>1318.872</td>
<td>1</td>
<td>1318.872</td>
<td>88.136</td>
<td>&lt;0.001</td>
<td>0.013</td>
</tr>
<tr>
<td>% Special education students</td>
<td>0.157</td>
<td>1</td>
<td>0.157</td>
<td>0.011</td>
<td>0.918</td>
<td>0.000</td>
</tr>
<tr>
<td>% Economically disadvantaged</td>
<td>46929.947</td>
<td>1</td>
<td>46929.947</td>
<td>3136.176</td>
<td>&lt;0.001</td>
<td>0.312</td>
</tr>
<tr>
<td>Average teacher experience</td>
<td>1234.023</td>
<td>1</td>
<td>1234.023</td>
<td>82.466</td>
<td>&lt;0.001</td>
<td>0.012</td>
</tr>
<tr>
<td>District expenditures - instruction per pupil (by thousands)</td>
<td>100.532</td>
<td>1</td>
<td>100.532</td>
<td>6.718</td>
<td>0.010</td>
<td>0.001</td>
</tr>
<tr>
<td>Expenditures - instructional equipment (log10 transformed)</td>
<td>88.109</td>
<td>1</td>
<td>88.109</td>
<td>5.888</td>
<td>0.015</td>
<td>0.001</td>
</tr>
<tr>
<td>District expenditures - instructional staff (log10 transformed)</td>
<td>2353.272</td>
<td>1</td>
<td>2353.272</td>
<td>157.262</td>
<td>&lt;0.001</td>
<td>0.022</td>
</tr>
<tr>
<td>Level 2 (district) subgroups</td>
<td>10591.811</td>
<td>3</td>
<td>3530.604</td>
<td>235.939</td>
<td>&lt;0.001</td>
<td>0.093</td>
</tr>
<tr>
<td>Error</td>
<td>103506.444</td>
<td>6917</td>
<td>14.964</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>40637371.000</td>
<td>6935</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table 3-8. Adjusted Means and P-Values for Level 1 (School-Level) Distal Outcomes

<table>
<thead>
<tr>
<th>Variable</th>
<th>CB4 Low STaR Districts (22.6%)</th>
<th>CB1 High STaR Districts (22.9%)</th>
<th>CB2 Moderate STaR Districts (34.6%)</th>
<th>CB3 Model STaR Districts (19.8%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted Mean</td>
<td>Adjusted Mean</td>
<td>Adjusted Mean</td>
<td>Adjusted Mean</td>
<td>Adjusted Mean</td>
</tr>
<tr>
<td>% STARR 2012</td>
<td>73.83</td>
<td>77.11</td>
<td>76.16***</td>
<td>77.60***</td>
</tr>
</tbody>
</table>

Note: *p < .10; *p ≤ .05; **p ≤ .01; ***p ≤ .001

150
Table 3-7 contains the ANCOVA results for the district level distal outcomes, controlling for the covariates, for the MLCA at Level 2 of the model. Results indicate a statistically significant main effect for the Level 2 district subgroups \[ F(1, 6917) = 3530.604, p < 0.001, \text{ partial } \eta^2 = 0.093 \] on the district percent proficient on the 2012 STARR/TEKS achievement tests. Most of the covariates, with the exception of extra-large schools and proportion of special education students, had a statistically significant influence on the dependent variable of percent pass rate on the 2012 Texas STARR/TEKS tests. Similarly to the school level covariates, the proportion of economically disadvantaged students within the district had the highest effect size among all of the covariates, significantly influencing the 2012 percent pass rate for the 2012 STARR/TEKS tests \[ F(1, 6917) = 3136.176, p < 0.001, \text{ partial } \eta^2 = 0.312 \] and indicating a small effect size according to Cohen’s guidelines (0.2 – small effect, 0.5 – moderate effect, 0.8 – large effect). Further, Table 3-8 presents the adjusted means for the district percent proficient on the 2012 Texas STARR/TEKS achievement tests, which show that the Low STaR Districts subtype \( (M = 73.83) \) have significantly lower standardized test score pass rates on the 2012 Texas STARR/TEKS assessment than the Moderate \( (M = 76.16) \), High \( (M = 77.11) \), and Model STaR Districts \( (M = 77.60) \) subgroups, when controlling for the district-level covariates.

**Discussion**

The aim of this study is to examine school and district leadership practices in Texas through the lens of technology leadership by utilizing multilevel latent class analysis (MLCA) to determine the extent to which there are different subgroups of teacher perceptions of technology leadership within the 2011-12 Texas School Technology and Readiness (STaR) Charts. Past research findings in educational leadership have focused on understanding the variation of leadership practice across diverse contexts, but research specifically on technology leadership,
and on the Texas \textit{STaR} Charts in particular, have offered conflicting insights how technology leadership, school contexts, and student outcomes can inform school change efforts with technology. The present study is one of the first studies to apply MLCA to Texas \textit{STaR} Chart data to empirically define a typology of different statistically significant subgroups of teacher perceptions of technology leadership at both the school and district levels in Texas, while also providing meaningful insights into the extent to which different school and district contexts in Texas are associated with certain perceptions of technology leadership practice. This study is also one of the first generalizable studies on Texas \textit{STaR} Chart data to provide evidence that positive perceptions of technology leadership are associated with higher student pass rates on the 2012 Texas standardized tests, while also finding that the multilevel typology model as a measure of teacher perceptions of technology leadership practice has a significant and independent effect on student achievement outcomes in Texas schools and districts.

The ordinal typology in the present study is aligned to the typology outlined in the original nationwide \textit{STaR} Chart Assessment report released over twenty years ago (CEO Forum on Education and Technology, 1997, 1999, 2000, 2001). Both the original 1997 \textit{STaR} Chart Assessment report and the results from the current study outline a typology of \textit{STaR} Chart responders in ordinal subgroups that share many common characteristics based on the \textit{STaR} Chart “Four Pillars” of \textit{hardware}, \textit{connectivity}, \textit{professional development}, and \textit{digital content} (CEO Forum on Education and Technology, 1997, 1999, 2000, 2001). For example, while teachers in schools and districts classified as \textit{High Tech} or \textit{Target Tech} in the original 1997 typology or \textit{High STaR} or \textit{Model STaR} in my MLCA typology note that their schools have pervasive access to new computer technology and educational software, ample opportunities for technology-related professional development, and strong digital instructional content that is
aligned to state standards, teachers in schools and districts in the *Mid Tech* or *Low Tech* in the 1997 *STaR* Chart report and the *Moderate STaR* and *Low STaR* subgroups identified within the 2011-12 Texas *STaR* Chart typology in the present study describe their schools as having antiquated computers and technology software, inadequate technology professional development, and limited digital content for students. Interestingly, although the response pattern on the *connectivity* pillar remained stratified across the ordinal subgroups in both typologies, most teachers describe their schools as having stronger Internet connectivity than the original 1997 report (see Figure 3-2). These findings could speak to the success of recent policy efforts to improve network infrastructure and to increase access to broadband and high-speed Internet for U.S. schools and districts, particularly in rural and low-income communities (U.S. Department of Education, 2014, 2016).

The findings from the present study also diverge from the findings in the original 1997 *STaR* Chart report in several ways. First, the present study differs from the original 1997 *STaR* Chart typology in the proportion of schools across the different subgroups. According to the original 1997 *STaR* Chart Report, only 3% of the schools were in the “Target Tech” subgroup (CEO Forum on Education and Technology, 1997). However, in the present study, I use MLCA to empirically define different statistically significant subgroups of schools and districts in Texas and show that over one-fifth of Texas schools and districts were in the top school (*High STaR Schools*) and district (*Model STaR Schools*) subgroups.

The second difference between the present study and the 1997 *STaR* Chart Assessment report is that the *STaR* Chart typology model reflects current conceptions of how educational leadership researchers define instructional leadership. Prior reviews of instructional leadership research (Boyce & Bowers, 2018b; Hallinger & Heck, 1996) have highlighted a conceptual shift
within the literature away from examining leadership behaviors (Hallinger & Murphy, 1985) toward investigating perceptions of leadership practice within shared, distributed framework that includes teachers and principals (Marks & Printy, 2003; Printy et al., 2009; Spillane, Halverson, & Diamond, 2001, 2004). As leaders often use their perceptions to guide their behaviors that directly influence the school itself and the teachers, and indirectly influence student achievement, understanding how principals, teachers, and the organization itself perceive leadership practice is an important conceptual and methodological factor to consider (Boyce & Bowers, 2018a; Goff et al., 2014; Hallinger & Heck, 2011; Halverson et al., 2014; Heck & Hallinger, 2009; Urick & Bowers, in press). Past research has used aggregate teacher perceptions of leadership, in particular, as a measure of leadership practice and as a proxy for measures of school-level leadership practices (Boyce & Bowers, 2018a; Leithwood & Jantzi, 2008; Urick & Bowers, in press). Using the MLCA framework to explore the variance between teacher perceptions of technology leadership through the STaR Chart data presented a unique opportunity to study technology leadership behaviors through the perceptions of teachers.

The third difference between the 1997 STaR Chart survey and the current study is that the 1997 STaR Charts ask teachers to rate their school based on the presence of the “Four Pillars” of hardware, connectivity, professional development, and digital content, all of which are strictly technology-focused pillars (CEO Forum on Education and Technology, 1997, 1999, 2000, 2001). However, recent research has pointed out that perceptions of technology leadership practices, rather than positive perceptions of the technology itself, are the largest predictor of positive technology-related instructional outcomes in schools (Anderson & Dexter, 2005; Dexter et al., 2009; McLeod & Richardson, 2013). Thus, I used technology leadership indicator variables from the Texas STaR Charts in the current study in order to explore the extent to which there are
different subgroups of perceptions of technology leadership across schools and how those subgroups aggregate to the district level. These variables were closely aligned to the empirically-validated CALL survey measuring perceptions of leadership for learning from both teachers and leaders (Blitz et al., 2014; Halverson et al., 2014). With the technology leadership lens from the Texas STaR Charts, my findings describing a three subgroup typology on technology leadership at the school level mirror research findings that also find multiple subgroups of teacher and leader perceptions of instructional leadership and leadership for learning (Bowers et al., 2017; Urick, 2016; Urick & Bowers, 2014b; Urick & Bowers, in press). Furthermore, at the district level, because much of the technology leadership literature focuses exclusively on the superintendent (Hartman & Procter, 2003; Larson, Miller, & Ribble, 2010; McLeod et al., 2015; Richardson & Sterrett, 2018), there is need for strong research that examines how varied perceptions of teachers inform district leadership practices and overall district effectiveness as well (Bowers, 2008; Honig, 2003, 2012). The present study is the first study to identify a statistically significant leadership typology at the district level, outlining four district subgroups of STaR Chart responses and the proportion of schools in each subgroup. These findings amplify the call in the educational leadership research to use more person-centered methodologies to measure and study leadership practice based on a set of leadership behaviors that crosscut multiple styles and perceptions of leadership (Bowers et al., 2017; Boyce & Bowers, 2018a; Hallinger & Heck, 2011; Heck & Hallinger, 2014; Leithwood & Jantzi, 2008; Leithwood, Patten, & Jantzi, 2010; Urick, 2016; Urick & Bowers, 2014a, 2014b; Urick & Bowers, in press) and to apply these methodologies to new conceptions of leadership, like technology leadership, in order to build stronger theoretical and methodological cohesion within educational leadership research (Wang, 2018; Wang & Bowers, 2016; Wang et al., 2017).
A fourth way that the present study differs from the original 1997 STaR Chart typology is that the STaR Chart typology model in the present study reflects current methodological advances in how educational leadership researchers measure instructional leadership. Past educational leadership research has employed multilevel methods to investigate how teachers and principals individually and collectively perceive instructional leadership. In a study examining the individual and collective perceptions of principal instructional leadership from teachers and principals using the Teaching and Learning International Survey (TALIS), Urick and Bowers (2017) found that teachers’ individual and collective perceptions of principal instructional leadership loaded on a single latent factor and were isomorphic from level 1 (individual) to level 2 (collective). In other words, teachers perceived principal instructional leadership only in simple, ordinal terms from high to low and that this unidimensional perception of leadership did not change when examining teachers’ perceptions of principal leadership individually or collectively when aggregated up to the school level. However, at the same time, in another study examining teachers’ perceptions of their own leadership for learning practices using multilevel factor analysis with large-scale teacher data from SASS, Boyce and Bowers (2018a) find that teachers had non-isomorphic conceptions of leadership for learning, as individual teachers understand leadership for learning as specific tasks and behaviors that are related to their teaching role, like taking attendance or parent involvement, and teachers collectively envision leadership for learning as an organizational function.

The findings from the present study support the conclusions of the Urick and Bowers (2017) study. Several recent studies using LCA find that teachers perceive technology use (Chapter 2, this volume) and instructional leadership (Bowers et al., 2017; Boyce & Bowers, 2018a; Marks & Printy, 2003; Printy et al., 2009; Urick, 2016; Urick & Bowers, 2014b; Urick &
Bowers, in press) in multidimensional, complex ways. My findings of three subgroups of teacher perceptions of technology leadership at the school level and four subgroups of district subgroups that follow an ordinal pattern of low to high may indicate that Texas teachers perceive technology leadership as its own separate construct from instructional leadership or technology use. However, these findings may also suggest that Texas teachers may conceptualize technology leadership as specific tasks and behaviors, rather than a deeper perception of technology leadership as a function of specific behaviors and the organizational context that influences how individuals enact these behaviors, as theorized in the larger educational leadership literature (Boyce & Bowers, 2018b; Hallinger, 2011; Marks & Printy, 2003; Printy et al., 2009; Spillane et al., 2001, 2004). While there is a wealth of studies exploring the multifaceted construct of teacher technology use in schools (Chapter 2, this volume), the ordinal solution from the findings of the present study support the call for more large-scale studies in technology leadership that explore perceptual variations in how teachers and leaders understand technology leadership.

The fifth way that my findings are a novel contribution to the 1997 STaR Chart report is that the present study is the first study to offer empirical evidence that good technology leadership is indeed good leadership across school and districts in Texas. In light of research that has documented the unique challenges that administrators face with technology leadership in the digital age (Peck, Mullen, Lashley, & Eldridge, 2011; Richardson et al., 2015; Sauers et al., 2014), resting on the assumption that technology leadership is just good leadership without generalizable evidence from large-scale data could be a lasting challenge for technology leadership researchers. Although the Texas STaR Charts are one of the only publically available large-scale data sets on technology leadership, past research on the STaR Charts (Davidson et al., 2014; Dawson & Rakes, 2003; Lea, 2016; Mishnick, 2017; Moore & Serfin, 2017; Plyler, 2017;
Tipton, 2015) has failed to reach any common substantive conclusions about technology leadership in Texas and its impact on student achievement. My findings suggest that the school level subgroups of Texas STaR Chart responses from teachers in my cross-sectional MLCA model at a single time point has a significant and independent effect on student achievement outcomes, accounting for approximately 2% of the variance on school percent pass rates. These findings speak to the question that Hallinger and Heck (1996) raised about how much leadership indirectly impacts student achievement and align with several mediated SEM studies and meta-analyses that find that school leadership has an average effect size of 0.12 on student achievement outcomes (Antoniou, 2013; Hendriks & Scheerens, 2013; Scheerens, 2012).

Similarly, I found that the district-level subgroups in my cross-sectional MLCA model also had a significant and independent effect on student achievement as well, explaining 9% of the variance on district pass rates on the 2012 Texas STARR/TEKS achievement tests. These findings align with studies in the body of district effectiveness research that finds district leadership impacted student achievement and had similar effect sizes in several states, like North Carolina (Chingos, Whitehurst, & Gallaher, 2015), Ohio, and Texas (Bowers, Ni, & Esswein, 2018). In all, the findings in this study represent the first generalizable evidence from statewide data that a leadership typology model framework to examine technology leadership is associated with a portion of the variance in Texas student achievement outcomes and for the first time gives an estimate of the direct effect of technology leadership on student achievement. My study reinforces past educational leadership research that argues that understanding the variation in leadership types across different contexts could help clarify the relationship between leadership and student achievement (Bowers et al., 2017; Boyce & Bowers, 2018a; Marks & Printy, 2003; Printy et al., 2009; Urick, 2016; Urick & Bowers, 2014b; Urick & Bowers, in press).
Also related to the link between technology leadership and student achievement, my findings also indicate that teachers in the *High STaR Schools* and the *Model STaR Districts* subgroups with the highest average perceptions of technology leadership have significantly higher percent pass rates on the 2012 Texas STARR/TEKS assessments than the other school and district subgroups. These findings tie into past research that shows that positive perceptions of technology leadership are associated with positive perceptions of overall leadership effectiveness (Weng & Tang, 2014) and that teacher perceptions matter when measuring leadership effectiveness (Goff et al., 2014; Hallinger & Heck, 2011; Heck & Hallinger, 2009; Urick & Bowers, in press).

Findings from the present study also indicate that certain community, demographic, and context variables are associated with certain subgroups of *STaR* Chart responses across Texas schools and districts. In terms of my school-level findings, I found that teachers in schools placed in the *High STaR Schools* subgroup were more likely to be urban high schools with low student-teacher ratios. My findings also indicated that the majority of teachers were placed in the *Moderate STaR Schools* subgroup and were more likely to be very large schools in towns or rural communities. This findings deviate from the CEO Forum on Education and Technology (1997) original *STaR* Chart report that placed the majority of schools in the *Low Tech* subgroup and could reflect recent policy efforts in Texas to improve teacher technology use in schools (Texas Education Agency, 2006). Finally, Texas teachers in schools within the *Low STaR Schools* subgroup were more likely to be very large middle schools with higher proportions of special education students and students from economically disadvantaged backgrounds. Within the four district level subgroups, the school subgroup types were unevenly distributed throughout the district subgroups. *Model STaR Districts* subgroups had the highest proportions of schools in the
*High STaR Schools* subgroup, while *Low STaR Districts* had the highest proportion of *Low STaR Schools*. Additionally, I also found large school districts were 10.49 times more to be in the *High STaR Schools* subgroup and that schools in the *Model STaR Districts* and *Moderate STaR Districts* subgroup were less likely to have larger proportions of African-American and Hispanic students. All of these findings speak to news coverage that continue to highlight a digital divide within Texas schools that proliferates a perceptual gap in how teachers and leaders that primarily serve historically marginalized students access new technologies, acquire new instructional resources, and experience technology leadership efforts (Bendici, 2017; Flahive, 2018). My findings show that the variance of teachers’ perceptions of technology leadership across schools and districts is not a random coincidence and presents additional evidence that there could also be a new type of digital divide in how teachers and leaders perceive, enact, and sustain technology leadership for school improvement. Further, these findings from Texas also reflect a larger trend in the United States and worldwide to find ways to empower school leaders to establish systems and processes that work to provide equal access to technology resources, digital content, and professional learning opportunities for teachers and leaders that could eliminate the educational and societal disparities of the digital divide within historically marginalized and disenfranchised communities. This study adds to the call to reconceptualize the digital divide as a social justice issue with both *distributional* and *relational* dimensions (Gewirtz, 2001; Horsford, 2016; North, 2006). In other words, instead of addressing the digital divide by only focusing on the equitable distribution of technology to schools and districts, leaders must also recognize perceptual differences in how teachers and leaders within schools and districts with diverse demographics and community contexts understand technology
leadership and how these sociocultural factors influence schools’ and districts’ relationship with technology-related instructional reform.

**Limitations**

One limitation of the current study is the structure and collection of the Texas *STaR* Chart data. There are currently no nationally generalizable datasets on technology leadership. The *STaR* Chart data I used for this study captures teachers’ perception of technology leadership and aggregates the data to the school and district level. Because of the narrow scope of the *STaR* Charts as a state self-assessment tool (Texas Education Agency, 2014), there is limited information on the data collection strategies, including information on how many teachers or school leaders completed the *STaR* Chart surveys within each school, when the data were actually collected during the 2011-2012 school year, and why certain school and districts did not fill out the *STaR* Charts. I recommend that future survey administrations with the *STaR* Chart collect data from teachers, principals, and other school and district leaders to examine the extent to which perceptions of technology leadership are aligned across schools and districts.

A second potential limitation is that there is limited documentation that outlines how district evaluators conducted any content or empirical validation of the Texas *STaR* Chart surveys. We attempted to address this issue by including variables that aligned with the empirically validated *CALL* survey (Halverson et al., 2014; Kelley & Halverson, 2012). Still, past research points to multilevel methods that utilize teacher and principal perceptions together in a single model as a helpful framework in eliciting more variation in how teachers and leaders perceive instructional leadership within their school or district contexts and provide a fuller picture of leadership practice (Boyce & Bowers, 2018a; Goff et al., 2014; Hallinger & Heck, 2011; Heck & Hallinger, 2009; Urick & Bowers, in press). I was unable to include principal
perceptions of technology leadership in the current study because Texas only administers the STaR Chart to teachers (Texas Education Agency, 2014) and because there are no other large-scale surveys that capture both teacher and principal perceptions of technology leadership within the same dataset. While researchers have developed a wealth of survey instruments that capture perceptions of teacher technology use as a multidimensional construct (Bebell, Russell, & O'Dwyer, 2004; O'Dwyer, Russell, & Bebell, 2004, 2005; Ritzhaupt et al., 2018), empirically validated measures or survey instruments measuring teacher and principal perceptions of technology leadership are virtually nonexistent. I encourage the Texas Education Agency to administer the STaR Chart survey to principals and district administrators in order to capture multiple perceptions of technology leadership in Texas schools and districts and to conduct multilevel factor analysis studies with the data in order to better understand how teachers, principals, and district leaders collectively and individually view technology leadership in Texas.

A third limitation of the current study is the specifications of the MLCA model. In general, the traditional three-step LCA approach is an additive method that progressively iterates through an unconditional model, a model with covariates, and a model with distal outcomes in a single omnibus model in order to ensure that the estimates are unbiased (Asparouhov & Muthén, 2014; Nylund-Gibson et al., 2014; Vermunt, 2010). With multilevel LCA, following recommendations from the literature (Asparouhov, 2018; Bowers et al., 2017; Henry & Muthén, 2010), I manually simulated this three-step approach to estimate covariates and distal outcomes. In comparing the omnibus model of LCA with my manual approach for MLCA, it is possible that manually specifying the MLCA could produce larger standard errors in statistics related to subgroup membership, covariates, and distal outcomes. I encourage more MLCA simulation
studies that seeks to develop an omnibus approach to estimating subgroups, covariates, and distal outcomes within a single multilevel model.

The fourth limitation of the study pertains to the distal outcomes. I found that my pre-analysis of the distal outcomes did not fulfill the assumptions of equal variances and homogeneity of regression (Mertler & Vannatta Reinhart, 2017). In terms of the equal variances assumption, one exception, according to the literature (Leech, Barrett, & Morgan, 2005), is to determine if the sample size of largest subgroup in the independent variable is not 1.5 times larger than the smallest subgroup in the data. I verified that the subgroups at the school and district levels fulfilled this exception before moving forward with the analysis. In terms of the homogeneity of regression assumption, in experimental studies, analysis of covariance is anchored in the assumption that the independent variable has been manipulated and that the covariates are independent from the dependent variable (Leech et al., 2005). However, as the present study is an observational study where the independent variable is not manipulated, I aim to use the ANCOVA results as a way to observe differences across the school and district subgroups, rather than to determine treatment effects. Further, in terms of using student achievement pass rates as distal outcomes, Ho (2008) finds that using percent proficiency metrics within state accountability data as a metric of student achievement offers a limited understanding of the distribution of test scores across schools and districts and that these data points often lead to incorrect inferences about student achievement. However, given the need to include distal outcomes and the limited publically accessible data on student achievement available from the Texas Education Agency, I included the percent pass rate on the 2012 Texas STARR/TEKS standardized tests as distal outcomes in the MLCA model at both the school and district levels as a consistent measure of student-level outcomes. I encourage states to consider reporting more
robust metrics for student achievement that allow for population-level analyses across subgroups of data, such as scale scores.

**Implications and Conclusions**

The present study offers strong evidence that *good technology leadership is indeed good leadership* in Texas, one of the most diverse policy locales in the United States. In identifying statistically significant subgroups at the school and district levels with the *STaR* Chart surveys, I found that teachers with the highest perceptions of technology leadership were associated with the highest percent pass rates on the 2012 Texas standardized tests. However, I also found that teachers who serve students in historically disadvantaged schools were more likely to be in schools and districts where teachers have low perceptions of technology leadership practice and significantly lower standardized test score pass rates. The present study reiterates the urgency for more research that utilizes critical perspectives of social justice as a conceptual lens to examine the impact of technology leadership on student, teacher, and leadership outcomes.

This study has several implications for research, policy, and practice. For research, Thompson, Sykes, and Skrla (2008) argue that examining conceptions of leadership within multiple levels of an instructional system, like at the school and district levels, could help identify “the conditions essential to improved and more equitable student performance [like] shared motivating goals, aligned capacity, and concentrated resources” (p. 7). This study demonstrates the exciting potential for educational leadership researchers not only to utilize new conceptual lenses to better understand the relationship between leadership and student achievement given the modern-day contexts that influence leadership practice, but also to employ multilevel methods, like MLCA, to deeply understand multiple leadership perceptions and their interactions with teachers and leaders across diverse school contexts. For policy, this
study has implications for policy makers as they craft educational technology policies with the aim of closing achievement gaps and championing educational equality. In her critique of policy makers in Texas, McNeil (2000b) writes that “equity is being seriously undermined because the State [of Texas] was allowed to substitute for equity a series of activities that give the appearance of sameness, regardless of their legal or educational merit” (p. 509). As Texas plans for long-term investments in educational technology in the future, my findings have strong implications for Texas policy makers as they develop a more holistic approach to use educational technology as a vehicle for educational equality throughout the state that could include improving resource allocation processes that aims for more equal distribution of resources, investing in professional development for teachers to improve the disparity in how teachers use technology, and preparing leaders to utilize culturally responsive approaches to leadership support their technology leadership efforts (Khalifa, Gooden, & Davis, 2016). For practice, this study pushes school leaders to actively evaluate how their leadership may perpetuate digital divides for students and teachers at home or at school. Researchers have proposed that equity audits are a useful tool for school leaders to evaluate how equity in teacher quality and the instructional program could facilitate equity in student achievement (Skrla, McKenzie, & Scheurich, 2009). Future studies examining how equity audits directly apply to technology use and technology leadership could be important contribution to mechanisms and tools that school and districts use to support their leadership in the digital age of schooling.
References


Tipton, M. A. (2015). *Analysis of the relationship between teachers' self-reported classroom technology implementation levels and high school students' academic achievement*. (Dissertation), Texas A&M University - Commerce.


Appendices

Appendix 3-A: Texas Campus School Technology and Readiness (STaR) Chart

Texas Campus STaR Chart Summary

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<tr>
<th>Campus (CD#): Timber Creek El (061902108)</th>
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<td>District: Lewisville ISD</td>
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<td>Email: <a href="mailto:heiers@lsd.net">heiers@lsd.net</a></td>
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### Key Area II: Educator Preparation and Development

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<th>L4</th>
<th>L5</th>
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### Key Area IV: Infrastructure for Technology

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**KEY AREA SUMMARY**

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<td>II. Educator Preparation and Development</td>
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<td>Advanced Tech</td>
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Completed Date: 12/7/2011
Printed: 6/25/2017 12:31 PM
### Appendix 3-B: Descriptives for School-Level Texas \( STaR \) Chart Indicators

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<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>STaR Chart Variable</th>
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<tr>
<td><strong>TL: Teaching and Learning</strong></td>
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<td></td>
</tr>
<tr>
<td>Patterns of classroom use</td>
<td>0</td>
<td>1</td>
<td>0.44</td>
<td>0.44</td>
<td>TL1; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Frequency/design of instructional setting</td>
<td>0</td>
<td>1</td>
<td>0.77</td>
<td>0.77</td>
<td>TL2; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Content area connections</td>
<td>0</td>
<td>1</td>
<td>0.75</td>
<td>0.75</td>
<td>TL3; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Technology applications (TEKS)</td>
<td>0</td>
<td>1</td>
<td>0.37</td>
<td>0.37</td>
<td>TL4; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Student mastery of technology applications (TEKS)</td>
<td>0</td>
<td>1</td>
<td>0.36</td>
<td>0.36</td>
<td>TL5; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td><strong>EP: Educator Preparation and Development</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Professional development experiences</td>
<td>0</td>
<td>1</td>
<td>0.46</td>
<td>0.46</td>
<td>EP1; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Models of professional development</td>
<td>0</td>
<td>1</td>
<td>0.35</td>
<td>0.35</td>
<td>EP2; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Capability of educators</td>
<td>0</td>
<td>1</td>
<td>0.35</td>
<td>0.35</td>
<td>EP3; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Technology professional development participation</td>
<td>0</td>
<td>1</td>
<td>0.23</td>
<td>0.23</td>
<td>EP4; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Levels of understanding and patterns of use</td>
<td>0</td>
<td>1</td>
<td>0.63</td>
<td>0.63</td>
<td>EP5; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td><strong>L: Leadership, Administration, and Instructional Support</strong></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Leadership and vision</td>
<td>0</td>
<td>1</td>
<td>0.69</td>
<td>0.69</td>
<td>L1; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Planning</td>
<td>0</td>
<td>1</td>
<td>0.51</td>
<td>0.51</td>
<td>L2; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Instructional support</td>
<td>0</td>
<td>1</td>
<td>0.41</td>
<td>0.41</td>
<td>L3; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Communication and collaboration</td>
<td>0</td>
<td>1</td>
<td>0.88</td>
<td>0.88</td>
<td>L4; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Budget</td>
<td>0</td>
<td>1</td>
<td>0.56</td>
<td>0.56</td>
<td>L5; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td><strong>INF: Infrastructure for Technology</strong></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Students per classroom computers</td>
<td>0</td>
<td>1</td>
<td>0.30</td>
<td>0.30</td>
<td>INT1; 1=Advanced / Target, 0=Developing / Early</td>
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<tr>
<td>Internet access connectivity</td>
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<td>0.98</td>
<td>0.98</td>
<td>INT2; 1=Advanced / Target, 0=Developing / Early</td>
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<td>Classroom technology</td>
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<td>0.56</td>
<td>0.56</td>
<td>INT3; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
<tr>
<td>Technical support</td>
<td>0</td>
<td>1</td>
<td>0.58</td>
<td>0.58</td>
<td>INT4; 1=Advanced / Target, 0=Developing / Early</td>
</tr>
</tbody>
</table>

\( N = 6,935 \)
Appendix 3-C: Descriptives for School-Level Covariates and Distal Outcomes

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<tr>
<th>Variable</th>
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<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>Dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Urbanicity (Ref group – City):</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Suburban</td>
<td>6935</td>
<td>0</td>
<td>1</td>
<td>0.19</td>
<td>0.40</td>
<td>CCD Universe Campus 11-12; ULOCAL, 21, 22, 23 = Suburb</td>
</tr>
<tr>
<td>Town</td>
<td>6935</td>
<td>0</td>
<td>1</td>
<td>0.13</td>
<td>0.33</td>
<td>CCD Universe Campus 11-12; ULOCAL, 31, 32, 33 = Town</td>
</tr>
<tr>
<td>Rural</td>
<td>6935</td>
<td>0</td>
<td>1</td>
<td>0.32</td>
<td>0.47</td>
<td>CCD Universe Campus 11-12; ULOCAL, 41, 42, 43 = Rural</td>
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<tr>
<td><strong>School level (Ref group – Elementary):</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Middle</td>
<td>6935</td>
<td>0</td>
<td>1</td>
<td>0.22</td>
<td>0.41</td>
<td>CCD Universe Campus 11-12; LEVEL, 2 = Middle</td>
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<tr>
<td>High</td>
<td>6935</td>
<td>0</td>
<td>1</td>
<td>0.17</td>
<td>0.38</td>
<td>CCD Universe Campus 11-12; LEVEL, 3 = High</td>
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<tr>
<td>Combined</td>
<td>6935</td>
<td>0</td>
<td>1</td>
<td>0.05</td>
<td>0.21</td>
<td>CCD Universe Campus 11-12; LEVEL, 4 = Other</td>
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<tr>
<td><strong>Enrollment (Ref group – Small):</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>6935</td>
<td>0</td>
<td>1</td>
<td>0.39</td>
<td>0.49</td>
<td>CCD Universe Campus 11-12; MEMBER, 601 - 1200 students</td>
</tr>
<tr>
<td>Large</td>
<td>6935</td>
<td>0</td>
<td>1</td>
<td>0.04</td>
<td>0.19</td>
<td>CCD Universe Campus 11-12; MEMBER, 1201-1800 students</td>
</tr>
<tr>
<td>Extra large</td>
<td>6935</td>
<td>0</td>
<td>1</td>
<td>0.04</td>
<td>0.20</td>
<td>CCD Universe Campus 11-12; MEMBER, &gt; 1801 students</td>
</tr>
<tr>
<td>% African-American students</td>
<td>6935</td>
<td>0</td>
<td>96.6</td>
<td>11.76</td>
<td>15.57</td>
<td>TEA AEIS 11-12; CPETBLAP</td>
</tr>
<tr>
<td>% Hispanic students</td>
<td>6935</td>
<td>0</td>
<td>100</td>
<td>49.11</td>
<td>30.24</td>
<td>TEA AEIS 11-12; CPETHISP</td>
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<tr>
<td>% Special education students</td>
<td>6935</td>
<td>0</td>
<td>100</td>
<td>9.23</td>
<td>6.17</td>
<td>TEA AEIS 11-12; CPETSPEP</td>
</tr>
<tr>
<td>% Economically disadvantaged</td>
<td>6935</td>
<td>0</td>
<td>100</td>
<td>62.34</td>
<td>25.66</td>
<td>TEA AEIS 11-12; CPETECOP</td>
</tr>
<tr>
<td>Student-teacher ratio</td>
<td>6935</td>
<td>0</td>
<td>45</td>
<td>14.92</td>
<td>3.36</td>
<td>TEA AEIS 11-12; CPSTKIDR</td>
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<tr>
<td>Average teacher experience</td>
<td>6935</td>
<td>2</td>
<td>33</td>
<td>12.03</td>
<td>2.88</td>
<td>TEA AEIS 11-12; CPSTEXPA</td>
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N = 6,935

<table>
<thead>
<tr>
<th>Variable</th>
<th>n</th>
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<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>Dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>% STARR/TEKS 2012 All Subjects</td>
<td>6506</td>
<td>3</td>
<td>100</td>
<td>75.15</td>
<td>12.03</td>
<td>TEA AEIS 2012;</td>
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N = 6,935
Appendix 3-D: Descriptives for District-Level Covariates and Distal Outcomes

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<th>Mean</th>
<th>SD</th>
<th>Dataset</th>
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<tr>
<td>City</td>
<td>910</td>
<td>0</td>
<td>1</td>
<td>0.07</td>
<td>0.26</td>
<td>CCD Universe District 11-12; ULOCAL, 11, 12, 13 = City</td>
</tr>
<tr>
<td>Suburban</td>
<td>910</td>
<td>0</td>
<td>1</td>
<td>0.08</td>
<td>0.27</td>
<td>CCD Universe District 11-12; ULOCAL, 21, 22, 23 = Suburb</td>
</tr>
<tr>
<td>Town</td>
<td>910</td>
<td>0</td>
<td>1</td>
<td>0.19</td>
<td>0.39</td>
<td>CCD Universe District 11-12; ULOCAL, 31, 32, 33 = Town</td>
</tr>
<tr>
<td><strong>Enrollment (Ref group – Small):</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>910</td>
<td>0</td>
<td>1</td>
<td>0.14</td>
<td>0.34</td>
<td>CCD Universe District 11-12; MEMBER, 1300-2399 students</td>
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<tr>
<td>Large</td>
<td>910</td>
<td>0</td>
<td>1</td>
<td>0.19</td>
<td>0.39</td>
<td>CCD Universe District 11-12; MEMBER, 2400 - 9999 students</td>
</tr>
<tr>
<td>Extra large</td>
<td>910</td>
<td>0</td>
<td>1</td>
<td>0.11</td>
<td>0.32</td>
<td>CCD Universe District 11-12; MEMBER, &gt;10000 students</td>
</tr>
<tr>
<td>% African-American students</td>
<td>910</td>
<td>0</td>
<td>85</td>
<td>7.21</td>
<td>10.92</td>
<td>TEA AEIS 11-12; DPETBLAP</td>
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<tr>
<td>% Hispanic students</td>
<td>910</td>
<td>0.7</td>
<td>99.8</td>
<td>37.14</td>
<td>26.81</td>
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<tr>
<td>% Special education students</td>
<td>910</td>
<td>0</td>
<td>100</td>
<td>58.57</td>
<td>17.84</td>
<td>TEA AEIS 11-12; DPETECOP</td>
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<tr>
<td>% Economically disadvantaged</td>
<td>910</td>
<td>1.4</td>
<td>24.4</td>
<td>9.47</td>
<td>2.46</td>
<td>TEA AEIS 11-12; DPETSPEP</td>
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<tr>
<td>Average teacher experience</td>
<td>910</td>
<td>4</td>
<td>20</td>
<td>12.84</td>
<td>2.26</td>
<td>TEA AEIS 11-12; DPSTEXPA</td>
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<td>910</td>
<td>3.94</td>
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<td>5.58</td>
<td>1.12</td>
<td>TEA AEIS 11-12; DPFEAINS (divided by 1,000)</td>
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<tr>
<td>instruction per pupil (by thousands)</td>
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<tr>
<td>Expenditures - equipment</td>
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<td>0</td>
<td>7.31</td>
<td>3.16</td>
<td>2.36</td>
<td>CCD Finance District 11-12; K09 (log10 transformed)</td>
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<tr>
<td>(transformed)</td>
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<tr>
<td>District expenditures -</td>
<td>910</td>
<td>0</td>
<td>7.98</td>
<td>5.46</td>
<td>0.98</td>
<td>CCD Finance District 11-12; E09 (log10 transformed)</td>
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<td>instructional staff</td>
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<tr>
<td>(transformed)</td>
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<tr>
<td><strong>N = 910</strong></td>
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<thead>
<tr>
<th>Variable</th>
<th>n</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>Dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>% STARR/TEKS 2012 All Subjects</td>
<td>910</td>
<td>46</td>
<td>97</td>
<td>76.13</td>
<td>7.96</td>
<td>TEA AEIS 2012;</td>
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</tbody>
</table>

N = 910
Appendix 3-E: MPlus Code for MLCA of Texas STaR Charts

TITLE: Texas STaR Chart LCA RUN 1, 2-LEVEL NON-PARAMETRIC LCA MODEL (NO CB INDICATORS)

DATA: FILE = C:\Users\keg2132\Desktop\1112_TEXASSTAR_SCHDIST_MPLUS_NODISTIND.dat;

VARIABLE:
NAMES = DIST_ID SCH_ID TL1_SCH TL2_SCH TL3_SCH TL4_SCH TL5_SCH EP1_SCH EP2_SCH EP3_SCH EP4_SCH EP5_SCH L1_SCH L2_SCH L3_SCH L4_SCH L5_SCH IN1_SCH IN2_SCH IN3_SCH IN4_SCH SUBURB TOWN RURAL MIDDLE HIGH MIXED MED LARGE XL AA HISP SPED ECONDIS RATIO TEACHEX S_MATH S_READ D_CITY D_SUBURB D_TOWN D_MED D_LARGE D_XL D_AA D_HISP D_ECOND D_SPED D_TEACH D_PUPIL D_EQUIP D_STAFF D_MATH D_READ;
MISSING = ALL(999) ;
IDVARIABLE = SCH_ID ;
USEVARIABLES = SCH_ID TL1_SCH TL2_SCH TL3_SCH TL4_SCH TL5_SCH EP1_SCH EP2_SCH EP3_SCH EP4_SCH EP5_SCH L1_SCH L2_SCH L3_SCH L4_SCH L5_SCH IN1_SCH IN2_SCH IN3_SCH IN4_SCH SUBURB TOWN RURAL MIDDLE HIGH MIXED MED LARGE XL AA HISP SPED ECONDIS RATIO TEACHEX D_CITY D_SUBURB D_TOWN D_MED D_LARGE D_XL D_AA D_HISP D_ECOND D_SPED D_TEACH D_PUPIL D_EQUIP D_STAFF ;
CATEGORICAL = TL1_SCH TL2_SCH TL3_SCH TL4_SCH TL5_SCH EP1_SCH EP2_SCH EP3_SCH EP4_SCH EP5_SCH L1_SCH L2_SCH L3_SCH L4_SCH L5_SCH IN1_SCH IN2_SCH IN3_SCH IN4_SCH ;
CLASSES = cb(4) cw(3);
BETWEEN = cb D_CITY D_SUBURB D_TOWN D_MED D_LARGE D_XL D_AA D_HISP D_ECOND D_SPED D_TEACH D_PUPIL D_EQUIP D_STAFF ;
CLUSTER = DIST_ID ;
WITHIN = TL1_SCH TL2_SCH TL3_SCH TL4_SCH TL5_SCH EP1_SCH EP2_SCH EP3_SCH EP4_SCH EP5_SCH L1_SCH L2_SCH L3_SCH L4_SCH L5_SCH IN1_SCH IN2_SCH IN3_SCH IN4_SCH SUBURB TOWN RURAL MIDDLE HIGH MIXED MED LARGE XL AA HISP SPED ECONDIS RATIO TEACHEX ;

MODEL:
\%WITHIN\%
\%OVERALL\%
cw ON SUBURB TOWN RURAL MIDDLE HIGH MIXED MED LARGE XL AA HISP SPED ECONDIS RATIO TEACHEX ;
\%BETWEEN\%
\%OVERALL\%
cb ON D_CITY D_SUBURB D_TOWN D_MED D_LARGE D_XL D_AA D_HISP
D_ECOND D_SPED D_TEACH
D_PUPIL D_EQUIP D_STAFF;

MODEL cw:
%WITHIN%
%cw#1%
[TTL1_SCH$1 TTL2_SCH$1 TL3_SCH$1 TL4_SCH$1 TL5_SCH$1 EP1_SCH$1
EP2_SCH$1 EP3_SCH$1 EP4_SCH$1 EP5_SCH$1];
[L1_SCH$1 L2_SCH$1 L3_SCH$1 L4_SCH$1 L5_SCH$1 IN1_SCH$1
IN2_SCH$1 IN3_SCH$1 IN4_SCH$1];

%cw#2%
[TTL1_SCH$1 TTL2_SCH$1 TL3_SCH$1 TL4_SCH$1 TL5_SCH$1 EP1_SCH$1
EP2_SCH$1 EP3_SCH$1 EP4_SCH$1 EP5_SCH$1];
[L1_SCH$1 L2_SCH$1 L3_SCH$1 L4_SCH$1 L5_SCH$1 IN1_SCH$1
IN2_SCH$1 IN3_SCH$1 IN4_SCH$1];

%cw#3%
[TTL1_SCH$1 TTL2_SCH$1 TL3_SCH$1 TL4_SCH$1 TL5_SCH$1 EP1_SCH$1
EP2_SCH$1 EP3_SCH$1 EP4_SCH$1 EP5_SCH$1];
[L1_SCH$1 L2_SCH$1 L3_SCH$1 L4_SCH$1 L5_SCH$1 IN1_SCH$1
IN2_SCH$1 IN3_SCH$1 IN4_SCH$1];

ANALYSIS:
TYPE = MIXTURE TWOLEVEL;
PROCESSORS = 8 (STARTS);
MITERATION = 5000;
STARTS = 20000 2000;
STITERATIONS = 100;

OUTPUT:
SAMPSTAT STANDARDIZED TECH1 TECH14 TECH7 TECH11 TECH12 TECH14;

PLOT:
TYPE = plot3 ;
SERIES = TL1_SCH TL2_SCH
   TL3_SCH TL4_SCH TL5_SCH EP1_SCH EP2_SCH
   EP3_SCH EP4_SCH EP5_SCH TL1_SCH
   L2_SCH L3_SCH L4_SCH L5_SCH IN1_SCH
   IN2_SCH IN3_SCH IN4_SCH(*);

SAVEDATA:
SAVE = CPROBABILITIES;
FILE = CPROBSSAV-2LEVEL-NODISTINT1.DAT;
FORMAT = FREE;
ESTIMATES = MIXESTIMATES-2LEVEL-NODISTINT1.DAT;
Appendix 3-F: SPSS Syntax for ANCOVA on Level 1 and Level 2 Distal Outcomes

Level 1 (School Level) Distal Outcomes:

UNIANOVA STARR_TES_TPASS__CAMPUS BY CW WITH SUBURB TOWN RURAL MIDDLE HIGH MIXED MEDIUM LARGE XL CPETBLAP CPETHISP CPETSPEP CPETECOP CPSTKIDR CPSTEXPA
/METHOD=STYPE(3)
/INTERCEPT=INCLUDE
/EMMEANS=TABLES(CW) WITH(SUBURB=MEAN TOWN=MEAN RURAL=MEAN MIDDLE=MEAN HIGH=MEAN MIXED=MEAN CPETBLAP=MEAN CPETHISP=MEAN CPETSPEP=MEAN CPETECOP=MEAN CPSTKIDR=MEAN CPSTEXPA=MEAN) COMPARE ADJ(BONFERRONI)
/PRINT DESCRIPTIVE PARAMETER HOMOGENEITY
/CITERIA=ALPHA(.05)
/DESIGN=SUBURB TOWN RURAL MIDDLE HIGH MIXED MEDIUM LARGE XL CPETBLAP CPETHISP CPETSPEP CPETECOP CPSTKIDR CPSTEXPA CW.

Level 2 (District Level) Distal Outcomes:

UNIANOVA SCH_ID BY CB WITH DCITY DSUBURB DTOWN D_MED D_LARGE D_XL DPETBLAP DPETHISP DPETECOP DPETSPEP DPSTEXPA DPUPIL DK09_LOG10 DE07_LOG10
/METHOD=STYPE(3)
/INTERCEPT=INCLUDE
/EMMEANS=TABLES(CB) WITH(DCITY=MEAN DSUBURB=MEAN DTOWN=MEAN D_MED=MEAN D_LARGE=MEAN D_XL=MEAN DPETBLAP=MEAN DPETHISP=MEAN DPETECOP=MEAN DPETSPEP=MEAN DPSTEXPA=MEAN DPUPIL=MEAN DK09_LOG10=MEAN DE07_LOG10=MEAN) COMPARE ADJ(BONFERRONI)
/PRINT DESCRIPTIVE PARAMETER HOMOGENEITY
/CITERIA=ALPHA(.05)
/DESIGN=DCITY DSUBURB DTOWN D_MED D_LARGE D_XL DPETBLAP DPETHISP DPETECOP DPETSPEP DPSTEXPA DPUPIL DPUPIL DK09_LOG10 DE07_LOG10 CB.
Appendix 3-G: Classification Probabilities for the Most Likely Class Membership (Column) by Latent Class (Row)

<table>
<thead>
<tr>
<th>Latent Class</th>
<th>Most Likely Class Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CW1</td>
</tr>
<tr>
<td>CW1 CB1</td>
<td>0.778</td>
</tr>
<tr>
<td>CW1 CB2</td>
<td>0.020</td>
</tr>
<tr>
<td>CW1 CB3</td>
<td>0.000</td>
</tr>
<tr>
<td>CW1 CB4</td>
<td>0.026</td>
</tr>
<tr>
<td>CW2 CB1</td>
<td>0.001</td>
</tr>
<tr>
<td>CW2 CB2</td>
<td>0.000</td>
</tr>
<tr>
<td>CW2 CB3</td>
<td>0.066</td>
</tr>
<tr>
<td>CW2 CB4</td>
<td>0.002</td>
</tr>
<tr>
<td>CW3 CB1</td>
<td>0.000</td>
</tr>
<tr>
<td>CW3 CB2</td>
<td>0.020</td>
</tr>
<tr>
<td>CW3 CB3</td>
<td>0.000</td>
</tr>
<tr>
<td>CW3 CB4</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Appendix 3-G is the classification probabilities for latent class membership for the MLCA. CW refers to the three-school-level subgroups. CB refers to the four district-level subgroups. The classification probabilities table shows the probability of individuals who belong to a certain subgroup being placed in that subgroup. The probabilities in the diagonal are greater than 0.75, and the probabilities in the off-diagonal cells are less than 0.1, which indicate good model fit.
Appendix 3-H: Indicator Plots of Level 1 Subgroups (School) in Level 2 Subgroups (District)

CB1 High STaR Districts (22.8%)

CB2 Moderate STaR Districts (34.6%)

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Chapter IV – ARTICLE THREE


**Purpose:** As school and district leaders grapple with the unfulfilled potential of technology’s impact on student achievement, as well as the deep-seeded systemic, cultural, and structural inequities that perpetuate new digital divides and complicate large-scale technology implementation efforts, there is a renewed mandate to rethink conceptions of technology leadership for school improvement. As such, the purpose of this study is to conduct a systematic review of literature in order to summarize and synthesize the extant literature that intersects the domains of technology, leadership, and culturally responsive education to inform a new integrated leadership framework called *technology leadership for social justice*. **Method:** Using a systematic, meta-narrative literature review methodology framework, I review 60 studies from 1975 to the present. I organize and code the articles based on Theoharis and Brooks (2012)’s equity-centered leadership framework of *access, process, and outcomes*, as well as a priori and emergent factors identified in previous reviews of literature. **Findings:** I find three themes across the literature: (1) resource control, (2) distributed leadership, and (3) sociocultural influences. This study outlines the major findings within each theme and integrates these findings into a single conceptual model. **Implications:** I describe this new conception of *technology leadership for social justice* as a framework that establishes cultural responsiveness and equity consciousness at the core of theoretical conceptions of technology leadership practice that could ultimately lead to improved student outcomes with technology. I discuss the implications of this new framework of *technology leadership for social justice* for future research, policy, and practice in educational leadership.
Introduction

In examining the impact of technology-based school reform, Cuban (2018) asserts, “They [schools and districts] know in their gut that no contemporary school district can reject the costs of new technology without being labeled Neanderthals” (p. 99). Indeed, over the last decade, school improvement efforts continue to highlight educational technology as one tool to elicit innovative and meaningful change in schools (U.S. Department of Education, 2010, 2016, 2017). While the majority of policy reforms and empirical research have focused on understanding the extent to which teachers use technology (Chapter 2, this volume), over the last two decades, there has been increased interest in the research literature to understand the scope and impact of school and district technology leadership on technology-focused school improvement efforts (Dexter, 2008; Flanagan & Jacobson, 2003; Richardson & Sterrett, 2018; Schrum, Galizio, & Ledesma, 2011; Thomas & Knezek, 1991). The body of school and district technology leadership research outlines that effective technology leaders should support teachers in using technology in student-centered ways that promote higher-order thinking and problem solving by building relationships with teachers, providing curricular leadership, designing professional development, and managing instructional resources (Dexter, 2008; Dexter, Richardson, & Nash, 2016; Richardson, Bathon, Flora, & Lewis, 2012; Richardson & Sterrett, 2018). Further, effective technology leaders must also work to build their own capacity to implement technology as they manage the organization (Beytekin, 2014; Dexter, 2008; Kearsley & Lynch, 1992; McLeod, Richardson, & Sauers, 2015; Thomas & Knezek, 1991). Most importantly, research finds that effective technology leadership can positively impact student achievement (Chapter 3, this volume), technology-related school outcomes (Anderson & Dexter, 2005), and perceptions of overall leadership effectiveness (Weng & Tang, 2014). While recent advances in technology
leadership research provide helpful insights into how school and district leaders can support
technology-focused instructional reform, one major criticism of the body of technology
leadership literature is that it is anchored in the assumption that technology leadership behaviors
“can be utilized without regard for cultural, political, or social concerns” (Kruger-Ross, 2013, p.
299). Although educational reformers have argued that educational technology can improve
instructional practice while also “shrink[ing] long-standing equity and accessibility gaps” (U.S.
Department of Education, 2017, p. 3), Collins and Halverson (2018) note that the educational
leadership field must work harder to fully articulate how leaders negotiate the new social,
cultural, and technological challenges of modern schooling. They write:

Forces for change, such as the civil rights emphasis on using schools to increase
social equity and the technological emphasis to open the core practices of schooling
to information technologies, push uncomfortably against conservative
stakeholders. Leaders who can effect real change need to understand where the
leverage points are in order to move the system […] Simply inserting technology
into high-poverty classrooms and schools, without considering how the contexts
for learning need to change, will likely fail. Leaders need to understand the power
of the new technologies, as well as the limits of instructional programs designed
only to raise test scores, to establish ambitious expectations for their communities.
(Collins & Halverson, 2018, p. xx)

In other words, even with the rise of technology in schools, certain schools, particularly
historically minoritized schools, continue to operate under a new digital divide, or a perpetual
system of structural and institutionalized inequality that prevents teachers and leaders in these
schools and districts from cultivating the ideal vision for technology integration (Chapter 2, this
volume; Chapter 3, this volume; Gorski, 2005; Valadez & Duran, 2007; Warschauer, 2016).
Because this fact, there is a need to better understand the theoretical and practical challenges of
technology leadership within the complex social and cultural context of 21st Century schooling,
beyond just encouraging educational leaders to champion digital equity by increasing access to
and buying more technology.
To address these lingering challenges of educational and digital inequality, advances in culturally responsive leadership could be a promising “action-based approach to creating school contexts and curriculum that respond effectively to the educational, social, political, and cultural needs of students” (Khalifa, Gooden, & Davis, 2016, p. 7). In fact, recent research has found that leaders who practice culturally responsive leadership can challenge the cultural and institutional norms that oppress historically minoritized communities while also boosting student achievement and engagement (Bustamante, Nelson, & Onweugbuzie, 2009; Deal & Peterson, 1999; Khalifa et al., 2016; Madhlangobe & Gordon, 2012; Peterson & Deal, 1998). However, even with promising outcomes of culturally responsive leadership approaches, Schwanenberger et al. (2013) still make the point that “[…] education leaders may be struggling to make deep connections between sociocultural and technology issues” (p. 39). Thus, to what extent could examining the literature that intersects the domains of technology, leadership, and culturally responsive social justice help address the new cultural, social and technological challenges that school and district leaders face in today’s schools?

The purpose of this study is to conduct a comprehensive and systematic review of literature intersecting the three domains of technology, leadership, and social justice in order to summarize what is known about school leadership within the challenges of the new digital divide and to synthesize the findings into a new integrated framework of technology leadership for social justice.

**Framework of the Study**

Recent investigations on school and district technology leadership practices have asserted that technology leadership, conceptually and practically, is just good leadership (Chapter 3, this volume; Richardson, McLeod, & Sauers, 2015). However, in light of the call for school and
district leaders to adopt more critical leadership approaches to school improvement that address larger systemic racial and economic inequalities that continue to perpetuate technological, cultural, and achievement divides (Chapter 2, this volume; Chapter 3, this volume; Horsford, Grosland, & Gunn, 2011; Khalifa et al., 2016; Scheurich et al., 2017), culturally responsive leadership has emerged as a form of leadership that “is not only liberatory and antioppressive, it is also affirmative and seeks to identify and institutionalize practices that affirm” (p. 1278). Culturally responsive leaders aim to build critical self-awareness, to create culturally responsive curricula and teacher preparation through conversations about culture, to promote culturally responsive and inclusive school environments, and to engage with the larger school community (Khalifa et al., 2016). With this unique charge, Theoharis (2007) insists that this type of “social justice leader[ship] goes beyond good leadership. Social justice in schools has not happened by chance. It takes more than what traditionally has been understood as good leadership to achieve greater equity” (p. 215). As such, using an equity-focused leadership framework to examine the body of technology leadership literature could provide new insights into how school and district leaders can utilize technology leadership to cultivate school improvement with technology, while also providing leaders with tools to holistically eliminate the consequences of digital inequity.

As a derivative of the larger culturally responsive leadership theory (Khalifa et al., 2016), Theoharis and Brooks (2012) theorize that employing an equity-oriented leadership framework to educational leadership research could help leaders “be concerned, committed, and effective in being both instructional and equity-oriented leaders” in their schools (p. 3). As such, I use the Theoharis and Brooks (2012) equity-oriented leadership framework to interrogate the literature base on technology, leadership, and culturally responsive education for three reasons.
First, the Theoharis and Brooks (2012) equity-oriented leadership framework contends that leaders must differentiate their leadership according to the specific content areas in order to deeply understand how to support instructional improvement in more equitable ways. Although building-level and district-level leaders cannot be specialists in every content area, Stein and Nelson (2003) argue that school and district leaders “must have some degree of understanding of the various subject areas under their purview…Administrators must be able to know strong instruction when they see it, to encourage it when they don’t, and to set the classroom conditions for continuous academic learning among their professional staffs” (p. 424). Recent investigations (Kanold, Briars, & Fennell, 2012; Lochmiller, 2016; Lochmiller & Acker-Hocevar, 2016) exploring the content-specific practices of principals who supervise secondary mathematics and science teachers have found that when principals focused their leadership efforts on supporting a specific content area, it helped them “identify potential barriers associated with improvement to content areas, create alternative strategies to improve instruction, and leverage strategies to improve instruction” (Lochmiller & Acker-Hocevar, 2016, p. 21). However, despite the fact that school and district leaders consistently report that they struggle with the specific challenges of technology leadership (Richardson & Sterrett, 2018; Sauers, Richardson, & McLeod, 2014), Theoharis and Brooks (2012) do not explore technology leadership within their framework. Therefore, employing the Theoharis and Brooks (2012) equity-centered leadership framework to the technology leadership literature could contribute to the growing body of research that examines how content-specific leadership can facilitate equitable instructional improvement.

Second, Theoharis and Brooks (2012) offer an equity-focused leadership framework that examine content-specific leadership practices in three key areas: access, process, and outcomes. I will now briefly define each of these areas. Access refers to the content-specific leadership
practices that ensure that all students have access to high-quality instruction and examines the extent to which high-quality material and human resources, high-quality informal and formal learning opportunities, and high-quality teaching are equitably distributed (Theoharis & Brooks, 2012). *Process* pertains to the ways in which leaders promote change through building and sustaining democratic processes in their decision making, such as establishing communication norms, encouraging teamwork and collaboration, and prioritizing transparent curricular and organizational restructuring (Theoharis & Brooks, 2012). The final area, *outcomes*, relates to the strategies that leaders use to measure and evaluate success related to student achievement, teacher growth and development, and leadership effectiveness. As both content area and school context could affect how leaders address issues of access, process, and outcomes in their schools, Theoharis and Brooks (2012) argue that examining content-specific leadership practices through this framework provides a more nuanced understanding of the overt and covert leadership practices that affect individual and organizational change.

Third, in response to the need for more robust reviews of literature within the larger educational leadership field (Hallinger, 2013), along with the need for more studies specifically focused on school and district technology leadership (Dexter et al., 2016; McLeod & Richardson, 2011; Richardson & Sterrett, 2018), there have been several comprehensive literature reviews exploring the breadth of technology leadership research coverage over the last two decades (Crompton, 2014; Dexter et al., 2016; McLeod & Richardson, 2011; Richardson et al., 2012; Richardson & Sterrett, 2018; Tan, 2010). The majority of these literature reviews organize their findings or implications based on the five core technology leadership practices outlined in the International Society of Technology in Education (ISTE, 2009) NETS-A Standards. However, because the purpose of this study is to examine the intersection of technology leadership and
social justice in order to frame technology leadership within the challenges of the new digital divide, organizing the findings based on the Theoharis and Brooks (2012) equity-oriented leadership framework of access, process, and outcomes could provide more critical perspectives on technology leadership practice and introduce a new social justice paradigm within this body of literature.

**Purpose and Research Questions**

Given the need to examine the body of technology leadership literature through an equity-oriented conceptual lens, the present study seeks to identify studies that explore the intersection of technology, leadership, and culturally responsive education and to synthesize these findings into a single conceptual framework. I use a systematic meta-narrative literature review methodology (Goodwin & Geddes, 2004; Gough, Oliver, & Thomas, 2012; Greenhalgh et al., 2009; Greenhalgh et al., 2004, 2005a; Hallinger, 2013; Wong et al., 2013) to answer the following research questions:

1) To what extent can major themes and relationships be identified within the selected body of literature focused on leadership, educational technology, and culturally responsive leadership approaches?

2) To what extent can these themes be integrated into a single conceptual model?

3) What are the theoretical, practical, and policy implications for an integrated framework of technology leadership for social justice?

**Methods**

I used a systematic, exploratory meta-narrative review methodology in the present study (Goodwin & Geddes, 2004; Gough et al., 2012; Greenhalgh et al., 2009; Greenhalgh et al., 2004, 2005a; Hallinger, 2013; Wong et al., 2013). The goal of systematic review is to systematically
organize and synthesize a bounded collection of prior literature in order to elicit new meaning within a selected domain (Hallinger, 2013). As such, I selected this method of inquiry for three reasons. First, exploratory reviews of literature “are most suitable when a problem or research domain is poorly understood and/or when relevant empirical research remains limited in scope” (Hallinger, 2013, p. 131). Second, because exploratory literature reviews address specific questions as identified by the researcher, the researcher is able to synthesize a body of literature on a topic and identify “intellectual dry holes” (Hallinger, 2013, p. 127) in a particular domain of interest. Third, Hallinger (2013) argues that systematic reviews are different from traditional literature reviews in four ways: (1) the researcher uses and reports explicit and transparent search methods; (2) the data collection and analysis follows a specific set of stages; (3) the method is accountable, replicable, verifiable, and updateable; and, (4) the method requires user involvement to ensure that studies are relevant and useful to the research question (p. 129). Because of these added standards, systematic reviews of literature are typically more rigorous, comprehensive, and robust than traditional reviews of literature (Hallinger, 2013).

Furthermore, meta-narrative review is a specific subtype of systematic review that lays out a roadmap of specific stages to follow to ensure that the review is systematic, purposeful, and exhaustive and that aims to provide rich descriptions of the findings (Goodwin & Geddes, 2004; Gough et al., 2012; Greenhalgh et al., 2009; Hallinger, 2013). Meta-narrative review helps researchers synthesize multiple domains of literature that are related, expansive, and conceptually complex (Goodwin & Geddes, 2004; Gough et al., 2012; Greenhalgh et al., 2009; Hallinger, 2013). Thus, given the purpose of meta-narrative review, as well as the call for more educational leadership research to employ systematic methods of review (Boyce & Bowers,
2018b; Hallinger, 2013), I determined that an exploratory, systematic meta-narrative literature review was the most suitable method for investigating the proposed research questions.

According to the literature, there are six stages of meta-narrative literature review: (1) the planning stage, (2) the search stage, (3) the mapping stage, (4) the appraisal stage, (5) the synthesis stage, and (6) the recommendations stage (Boyce & Bowers, 2018b; Greenhalgh et al., 2009; Greenhalgh et al., 2005b). First, the planning stage is where researchers create a set of open-ended research questions and search criteria to use based on an initial review of the body of literature of interest. The researcher can identify specific search criteria such as key words, date of publication, literature type (e.g., journal, book, dissertation), or empirical method. Next, during the search stage, the researcher uses the selected search criteria to conduct a systematic search for the relevant literature to include in the analysis. The search stage may require multiple iterations to narrow down the relevant literature based on the search criteria. The third stage, the mapping stage, involves the researcher using emergent or a priori codes to identify, construct, and analyze the conceptual, theoretical, or methodological connections among the selected literature. Fourth, at the appraisal stage, the researcher evaluates each of the selected studies and then organizes the codes generated in the mapping stage into larger themes. Next, the synthesis stage involves outlining all of the major themes and providing a narrative summary of the findings within each theme under a specific organizing framework. Finally, in the sixth stage, the recommendations stage, the researcher summarizes the findings in order to discuss relevant implications to research, theory, and practice. I will now describe how I addressed each of the six stages of systematic meta-narrative review in the present study.

The planning stage of the study consisted of reviewing the first two chapters of this manuscript, as well as several of the existing literature reviews on technology leadership.
Examining the findings from these studies allowed me to develop the purpose of the review, find a guiding theoretical framework, and outline specific research questions.

For the search stage, once again, I looked to past reviews in the technology leadership research literature to guide my search strategy. Although there is a more recent review of the technology leadership literature that focuses specifically on award-winning district technology leaders (Richardson & Sterrett, 2018), I found that the Dexter et al. (2016) study provided the most comprehensive review of the technology leadership literature to date. Similarly to the Dexter et al. (2016) study, my search strategy only included articles that were from peer-reviewed journals. However, my search strategy differs from the Dexter et al. (2016) study in three ways: (1) range of publication dates, (2) empirical methods used in the study, and (3) the overall theoretical framework. First, Dexter et al. (2016) bounded their search to research studies published between 1998 and 2015. In order to ensure that I was as expansive as possible with the search criteria, I decided to expand the search range to include literature written between 1945 and 2017, as most historical analyses list the year 1945 as the year that researchers most likely coined the term ‘educational technology’ (Reiser, 2001). The second difference between the Dexter et al. (2016) literature review and the present study is that I included peer-reviewed journal articles that included either qualitative, quantitative, or conceptual analyses. While the Dexter et al. (2016) only includes articles that discuss empirical results, I decided to include conceptual articles in the analysis to address the critique that there is a dearth of theory-driven research to inform best practices within the technology leadership research literature (McLeod & Richardson, 2011; Sauers et al., 2014; Wang, 2018). Finally, the third difference between the Dexter et al. (2016) literature review and the present study is that I used an equity-oriented leadership framework (Theoharis & Brooks, 2012) as the organizing framework to support the
overall purpose of the study to explore the intersection of technology, leadership, and social justice. In summary, I used the following inclusion criteria for the present study: (a) investigated the intersection of educational technology, K-12 school leadership, and culturally responsive practices, equity, and social justice; (b) published between 1945 and 2017; (c) labeled as a peer-reviewed, scholarly article; and, (d) included at least one mode of either qualitative, quantitative, or conceptual analysis.

I started the literature selection process with several rounds of search and review. After each review, I added more detailed criteria in order to ensure that my search was comprehensive. I started my search by querying five education-focused online databases: EBSCOHost (which includes H.W. Wilson and ERIC), JSTOR, Scopus, ProQuest (which includes ERIC), and WorldCat. For the first search query, I limited the publication date range from 1945 to 2017, but I did not limit the search to include only peer-reviewed journals in order to understand the expansiveness of the body of literature on the topic. My initial search string was “((‘instructional technology’ OR ‘school technology’ OR ‘educational technology’) AND ((‘principal’ OR ‘school principal’ OR ‘administrator’ OR ‘management’ OR ‘school leader’ or ‘leadership’)) AND (‘equity’ OR ‘social justice’)).” This search generated 21,324 results.

In the second search query, with the publication date range still set, I now limited the search to online include peer-reviewed articles and used wildcard search terms (marked with an asterisk) to capture any additional studies that could have been omitted. The second search string was “((‘instructional technology’ OR ‘school technology’ OR ‘educational technology’) AND OR ‘school principal’ OR ‘administrator’ OR ‘management’ OR ‘school leader’ or ‘leadership’)) AND (‘equity’ OR ‘equality’ OR ‘social justice’ OR ‘digital divide’
OR ‘culture’)).” This search generated 4,139 non-mutually exclusive results. After deleting duplicates, there were a total of 3,438 peer-reviewed research studies.

I then reviewed the titles of all 3,438 studies. In evaluating titles, I used four content criteria to sort through the results in order to determine the studies for further review: (a) related to K-12 schools, (b) related to educational or instructional technology, (c) related to educational leadership, or (4) related to technological equity, social justice, or cultural responsiveness. I included any title that referenced one of those topics in the subsequent stages of the search process. This step resulted in 636 studies still eligible for future analysis. I then read the abstracts of the remaining studies with a closer look at how the studies met the content criteria. The abstract read resulted in 148 studies remaining for further consideration.

I conducted the first full read of all 148 studies, focusing on the study’s research questions, methodologies, theoretical or conceptual frameworks, results, as well as the discussion and implications. I removed studies if they did not meet the content or selection criteria previously mentioned above. After the first full read, 72 studies remained in the corpus of relevant research studies. For the second full read, I focused on whether the studies explored some aspect of culturally responsive leadership or social justice. This second full read resulted in 60 studies that met the content, methodological, and theoretical criteria for the next stage. The mapping stage included several additional full reads of the 60 final articles selected for the study, as well as several rounds of coding and theming. After completing the third full read, I used the 28 dimensions outlined in the conceptual framework that the Dexter et al. (2016) literature review (see Hitt & Tucker, 2016) utilized to organize their findings as a priori codes to help identify patterns within the selected studies and to anchor my study with previous reviews of literature. After the coding process, I generated themes across the literature based on these
codes. I then reorganized the studies, along with the corresponding codes and themes, based on the Theoharis and Brooks (2012) framework of access, process, and outcomes and generated additional themes within each facet. While reviewing the codes and themes, I also maintained analytic summaries that noted areas of agreement and disagreement within each theme.

The appraisal phase of the study included a fourth full read of the 60 research studies, as well as a review of the codes and themes generated from the mapping stage. To review the literature selected for the study, I created a summary table of each study that included the author name, year of publication, literature type, journal, methods used, and key findings or conclusions. I also generated a matrix table that organized three major themes within the selected studies across the three facets of the Theoharis and Brooks (2012) framework of access, process, and outcomes. A full table of studies I included in the present study is located in Appendix 4-A.

Results

I now present the results from the synthesis stage of the meta-narrative literature review. As noted above, the synthesis stage provides narrative summaries and analysis of major themes across the 60 studies that intersect the domains of technology, leadership, and social justice. The three themes I identified across the literature are: (1) resource control, (2) distributed leadership, and (3) sociocultural influences. Table 4-1 provides a matrix table of the total number of studies under each of the four themes, as well as across each of the three facets of the Theoharis and Brooks (2012) framework. I conclude the results section with an integrated conceptual model of the findings.
Table 4-1. Matrix of Total Number of Studies across Four Major Themes and the Theoharis and Brooks (2012) Framework

<table>
<thead>
<tr>
<th>Theoharis and Brooks (2012) Equity-Oriented Leadership Framework</th>
<th>Number of Studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Access: distribution of resources, opportunities, and high-quality teaching</td>
<td>Resource Control</td>
</tr>
<tr>
<td></td>
<td>26</td>
</tr>
<tr>
<td>Process: promoting change through democratic decision-making</td>
<td>24</td>
</tr>
<tr>
<td>Outcomes: strategies to measure and evaluate success</td>
<td>10</td>
</tr>
</tbody>
</table>

*Note: If applicable, some studies have been categorized under more than one theme.

Appendix 4-B delineates how each article in the review was organized based on the Theoharis and Brooks (2012) framework, as well as the three themes of resource control, distributed leadership, and sociocultural influences. The majority of the studies selected for this study examine the intersection of technology, leadership, and social justice across different time points, geographical regions, and community and demographics contexts. There was also a wide variety in the sample sizes of the studies, ranging from an ethnography of one school leader to several cross-case studies of teachers, leaders, and schools. Qualitative interviewing and survey methods were the most commonly used methodologies in this subset of literature.

I will describe the themes in the order listed in Table 4-1, starting with resource control, and then describing the themes of distributed leadership and sociocultural influences, respectively. For each theme, I will start with a brief description of the theme, connecting it to prior knowledge in literature base in technology, leadership, and social justice. After describing the theme, I then organize the findings under each of these major themes using the Theoharis and Brooks (2012) equity-oriented leadership framework of access, process, and outcomes to surface areas of agreement and tension across the literature within each theme. Finally, I conclude each section by providing a brief summary of the findings under each theme.
Theme 1: Resource Control

**Description of theme.** The theme with the largest amount of related studies explored how school and district technology leaders control resources. Within the larger educational leadership literature, recent conceptions of leadership for learning theory argue that highly effective school leaders work to locate, acquire, and use resources that support student achievement growth (Boyce & Bowers, 2018b; Murphy, Elliott, Goldring, & Porter, 2007). These resources can be *material* resources, such as funding streams, instructional programs, and educational tools, or *human* resources that exist inside or outside the organization (Bowers, 2008; Murphy et al., 2007). Recent studies have suggested that the resource management practices of school leaders can have a greater influence on student achievement outcomes than other instructional leadership behaviors (Grissom & Loeb, 2011; Urick, 2016a) and that the scope and impact of these resources on school improvement depends on the extent to which leaders connect material and human resource allocation to the school’s instructional goals (Murphy et al., 2007). However, Darling-Hammond (2013) warns that “much less attention […] is paid to the *opportunity gap*, [or] the cumulative differences in access to key educational resources that support learning at home and at school: expert teachers, personalized attention, high-quality curriculum opportunities, good educational materials, and plentiful information resources” (p. 77). Systemic inequalities and discrimination have often mitigated who has access to high-quality resources and how these resources are allocated among schools and districts.

In a similar manner, as detailed below, school and district technology leaders must contend with managing resources that support the overall instructional goals of technology integration efforts. Most of the literature under this theme refers to inequality in the distribution of material resources, rather than human resources. More specifically, the literature describes
disparities in the quantity and quality of accessing technology resources, conflicting processes and policies governing how schools acquire technology resources, and the lack of evidence-based allocation models that provide a clear rationale in how the distribution of resources leads to improved student and teacher outcomes.

**Access and resource control.** Of the studies at the intersection of access and resource control, Table 4-1 indicates that 26 studies examined the differences in how school leaders access technology-related resources, particularly material resources. Recent case studies on eight award-winning secondary schools and districts find that technology leaders in these schools and districts often resort to very creative financial measures to provide ubiquitous access to technology for students and teachers (Levin & Schrum, 2013, 2014). At the school level, principals report using several cost-effective practices to purchase new technology, including reallocating monies from textbook budgets to buy digital instructional resources, leasing laptops instead of buying computers, renting out school spaces to increase the technology budget, or even using building funds to upgrade the technical infrastructure (Levin & Schrum, 2013, 2014). Similarly, at the district level, superintendents in these award-winning districts also report that they try to advocate to the school board to purchase bonds earmarked for technology or increase taxes to fund new technology purchases in order to defer costs to individual schools (Levin & Schrum, 2013, 2014). However, despite the fact that leaders in the exemplary schools and districts in the Levin and Schrum (2013, 2014) studies have control over several avenues to purchase and fund new technology initiatives, Garland (2009) warns that most other school leaders face monumental challenges with acquiring new funding and with controlling how the funding is allocated.
Research on the digital divide in schools have noted that school leaders should be acutely aware of issues of equity and access, regardless of their school’s or district’s financial standing (Flanagan & Jacobson, 2003; Garland, 2009). In fact, in a Delphi study that asked school leaders, researchers, and policymakers to rate and create a list of the top priorities for technology use in schools, equity of access emerged as one of their top concerns (Clark, 2006). Yet, although leaders are concerned with ensuring that teachers and principals have access to technology, the majority of literature exploring issues of access and resource control continue to document disparities in how leaders within certain schools and communities access the technology resources they need for their technology implementation efforts. The inequalities highlighted in the literature exist across several factors, including geography, school type, urbanicity, disability, race, socioeconomic status, and gender. I now describe how the studies under each of these social identifiers highlight issues of resource inequity.

**Geography.** Seven studies specifically explore the challenges that principals in developing countries face with obtaining and maintaining technology resources in their schools. In countries, such as Bahrain (Razzak, 2013), Chile (Blignaut, Hinostroza, Els, & Burn, 2010), South Africa (Blignaut et al., 2010; Mentz & Mentz, 2003), Taiwan (Chang, Chin, & Hsu, 2008), Turkey (Sincer, 2013), and Uganda (Newby, Hite, Hite, & Mugimu, 2012), principals consistently report similar barriers to technology implementation, including outdated or neglected technical infrastructure, insufficient financial support, limited budgets, overdue maintenance on computer hardware, and vandalism. Although digital inequality continue to challenge school leaders in developing countries, the majority of the literature that I found on access and resource control highlight digital inequalities within developed countries, like the United States and Canada. In developed countries, most of the studies can be disaggregated by
certain social identifiers like urbancity, school type, general and special education, socioeconomic status, race, and gender.

**Urbanicity.** Most studies exploring differences in resource access in developed countries compare access by urbanicity. Researchers have found that rural schools were less likely to have computers, Internet connectivity, funding, or leadership support due to high levels of poverty and isolation (Becker, 2006; Hannum, Irvin, Banks, & Farmer, 2009; Leonard & Leonard, 2006; Richardson & McLeod, 2011). Likewise, urban schools in the United States and Canada face similar challenges in obtaining funding to maintain the technology infrastructure (Gooden, 2005; Rabah, 2015). An investigation of Quebec English Schools in Canada found that principals in these schools face significant roadblocks in securing funding for technology and maintaining the school building infrastructure (Rabah, 2015). Similarly, in an ethnographic study exploring the leadership of an African-American principal in a U.S. urban information technology high school, Gooden (2005) noted that despite the school’s partnership with a major technology company, the principal still had to demand for physical improvements to the school’s infrastructure.

**School type, socioeconomic status, race, and gender.** Specifically in the U.S. context, researchers have also found that school type, socioeconomic status, race, and gender also impacts access to resources. Pertaining to school type, Anderson and Dexter (2005) found that principals in private schools rated their technology leadership lower than principals in public schools primarily due to the fact that principals in private schools were less likely to have the financial support of a school district. Related to differences in resource access by socioeconomic status, although principals in low-income schools were more likely to secure funding through school improvement grants, poorer schools are still less likely to have access to technology (Anderson & Dexter, 2005; Becker, 2006; Richardson & McLeod, 2011). Even race and gender remain two
factors that contribute to the inequitable distribution of resources. Research indicates that African-American (Becker, 2006) and transnational Latinx (Sanchez & Salazar, 2012) families have traditionally struggled to access technology resources at home and at school. Pertaining to gender, in a past survey of California school principals, Bayer (1984) finds that male principals were more technologically-oriented and less concerned with diversity than female principals. Quilling (1999) also adds schools generally struggle to provide equitable access to computers to young women and girls in school.

**Special education.** Four articles described the specific challenges that special education classrooms face when accessing technology-related resources. In the late 1980s, over half of the special education administrators in California reported that they had no computers for their special education classrooms (Goldman et al., 1987). As a result, in 1998, policy makers passed the Assistive Technology Act of 1998, which provided extra funding for schools to purchase assistive technology related to the specifications outlined in special education students’ Individualized Education Plans (IEPs) (Dyal, Carpenter, & Wright, 2009). As school leaders are often responsible for managing and executing IEPs for students, several authors note that it the ethical responsibility of modern-day school technology leaders to ensure that they understand the laws governing assistive technology use (Dyal et al., 2009), lean on teacher leaders, like school librarians, to purchase and manage electronic resources that teachers can use as accommodations for the general and special education classroom (Ennis-Cole & Smith, 2011), and advocate for increased access to and funding for new assistive technologies (Garland, 2009).

Although the literature highlights several disparities across demographic variables, some argue issues of technology access are minimal. For example, in two studies that examined technology use specifically in Catholic schools in Illinois, principals reported that they were
satisfied with the amount of technology and that inequities in computer access within and between schools were minimal (Dosen, Gibbs, Guerrero, & McDevitt, 2004; Gibbs, Dosen, & Guerrero, 2008). While most of the studies would agree with the assertion that Garland (2009) makes about how “the principal has a duty to become an informed activist in promoting access to technology by all students and teachers [and] must be aware of diversity issues, such as race, language, disability, and gender” (p. 40), it is still unclear from the literature on how school and district leaders would proceed with actually addressing these issues of access.

The literature examining the intersection of access and resource control reveal disparities across several social identifiers, including geographic, urbanicity, school type, socioeconomic status, race, gender, and special education status. Although several case studies of exemplary schools and districts offer unique ways for leaders to provide equitable access to technology, the studies organized under access and resource control primarily explain the breadth of the problem, rather than provide theories of action to guide school leaders in addressing issues of resource allocation inequity within their schools and districts.

**Process and resource control.** As outlined in Table 4-1, there were a total of 24 studies that documented the successes and challenges that school leaders encounter when establishing equitable processes for acquiring and managing their technology resources. As educational leadership research entered academic spheres in the early 1970s, Wood (1973) anticipated that the principals of the future must “know the make-up of a good system design to utilize the educational technology within his [or her] building” (p. 41). For some practicing school and district technology leaders, establishing good systems design involved making decisions and then bringing other stakeholders, such as teachers, parents, and district personnel, into the technology purchasing process in order to increase transparency and establish a culture of ownership and
accountability (Jackson & Deal, 1985; Mentz & Mentz, 2003). For others, the complex organizational structure of schools and districts complicated efforts to establish protocols and processes for acquiring new technology (Merriman, 1986; Shuldman, 2004). Consequently, systems thinking emerged as a popular conceptual framework that researchers offered to support school leaders as they plan for technology-related school improvement efforts. In defining systems thinking, Levin and Schrum (2013) offer a jigsaw puzzle metaphor for school and district technology leaders to consider:

Because schools and districts are organizational systems embedded in larger complex systems made up of interacting, interrelated, and interdependent components, taking a systems approach means that all the parts of the system have to be addressed in concert…acknowledging that adding one component (such as technology) to a system disturbs other parts of the system. Further, adding to or changing just one part of the system will change it, although usually not enough to make a real difference in the entire system, as has been seen in other studies about technology integration. (p. 30)

In other words, approaching technology leadership through a systems thinking lens requires leaders to understand the relationships between core aspects of the school organization – students, teachers, leaders, parents, and community – and how, if at all, the introduction of technology resources may enhance, interrupt, or influence these relationships (Levin & Schrum, 2013, 2014). However, while the literature that explores exemplary school districts offer this conception of systems thinking as an approach that school leaders can use, much of the literature exploring how the processes that school leaders use to manage technology resources raises questions about the practicality of systems thinking for school leaders as there is a wide variance in how schools and districts establish decision-making processes.

One tension in the literature on technology and systems thinking is the extent to which the principal or superintendent is directly involved in controlling the flow of resources. Anderson and Dexter (2005) argue that “technology leaders must be actively involved with technology…to
determine the degree to which the school has adequate technology goals, policies, committees, and supporting elements in place and where they should begin” (p. 74). The literature offers some concrete examples from various districts on how school and district leaders participate in acquiring resources. In one example, Levin and Schrum (2013, 2014) note that principals in the award-winning districts note that they leverage their connections with local businesses and organizations that can donate technology or establish sponsored partnerships for pilot technology program. Similarly, in a case study in one high school in the Southeastern region of the United States, Peck, Mullen, Lashley, and Eldridge (2011) noted that school leaders were instrumental in purchasing new technology and creating long-term financial support, teacher professional development, and leadership support systems to ensure that the technology initiative was sustainable. Even if senior administrators cannot directly support technology-related initiatives in their schools, Razzak (2013) offers that in Bahrain, assistant principals often help their principals to manage technology resources and allocate technology to classrooms.

Although administrators often assume responsibility for technology-related decision making in their schools, the literature also provides conflicting accounts on the role and influence of the principal in establishing control over the resource allocation process. At the school level, in outlining their conditions for successful classroom innovation, Zhao, Pugh, Sheldon, and Byers (2002) mention that the most successful instructional innovations in the schools that they investigated actually required little to no intervention from the principal and that leaders realized that their intervention would actually distract or impede from teachers taking ownership of the technology and from seeking out professional development to use technology effectively and meaningfully. Likewise, at the policy level where many technology purchasing decisions often originate, Nance (2003) finds that despite the push to have principal
and superintendents involved in technology policy, school administrators are minimally involved in technology decision making at the district level and not involved at all at the state and federal levels. Nance (2003) also notes that administrators’ participation in the educational technology policy process is a function of their school context as well, as he finds that urban principals were less likely than suburban or rural principals to participate in the policy process.

This conflicting perspective in the literature about the ways in which principals are directly involved in creating processes to control resource flow raises intriguing questions about the reasons why certain leaders might be more involved than others. In a study examining the philosophical assumptions of technology leaders and how their assumptions influence their decision making, Webster (2017) argues that sometimes the process itself – and the individuals within this system – put undue pressure on school and district leaders to make quick decisions about the technologies they adopt without research evidence or time to evaluate the impact of the technology on teaching and learning. In fact, in a study of New Hampshire superintendents, Shuldman (2004) notes that superintendents were very hesitant to spend funding on technology professional development for teachers because “using public money that would place technology directly in the hands of teachers…before placing it in the hands of students was, and remains, a touchy political proposition. Public tax payers would rather see technology in the hands of students – perhaps at the expense of – teachers learning how to use it” (p. 336). As a result, this constant pressure sometimes results in leaders pushing away their technology leadership responsibilities to another person or avoiding establishing protocols and procedures altogether, especially if there are budgetary limitations or unnecessary bureaucratic structures impede their ability to purchase technologies they want (Brown & Jacobson, 2016; Nance, 2003).
Similarly, the literature also documents the frustration that many leaders face in negotiating the conflicting purchasing processes that they want to establish in their schools and the processes that the district wants them to adopt. The majority of technology-related instructional initiatives start at the district level. Particularly related to special education, Dyal et al. (2009) states that it is the responsibility of the local school district to pay for assistive technology for special education students and that special education teachers and libraries often work closely with district personnel to determine what technologies they need (Ennis-Cole & Smith, 2011; Goldman et al., 1987). However, outside of special education, several studies document the frustrations that school leaders in historically underserved schools have when implementing large-scale technology initiatives from the district. For example, in a cross-case analysis of five middle schools with laptop programs, Dexter (2011) noted that some of the lower income schools struggled to implement technology because of miscommunication between the district model for a one-to-one computing laptop program and the distribution model that leaders in schools used to pass out laptops to students. Similarly, in a related study on rural school districts that adopted distance education coursework, Hannum et al. (2009) found that many leaders realized that the distance education courses offered by the district did not help students meet the state curriculum standards or graduation requirements.

Some of the apprehension that school leaders in certain communities face in building proper resource allocation processes are highly political. In Turkey, principals report that they do not have the necessary resources they need to integrate technology, and as a result, they often ask parents for technology donations (Sincer, 2013). However, Sincer (2013) reports that the Turkish Ministry of Education bans parent donations to schools and that some principals’ careers have been ruined because they accepted an illegal financial contributions. In Canada, principals in
Quebec English schools note that the Ministry of Education often restricts funding streams and vendors that they can use to purchase new technologies (Rabah, 2015). Within the U.S. context, Maddux (1997) mentions that as U.S. schools started to invest in Internet infrastructure, she found that most teachers could not convince their administrators to place phone lines in classrooms. Even in later years when the technology became more commonplace, Richardson and McLeod (2011) reveal that although principals in Native American schools continue to struggle with outdated computers, crumbling infrastructure, and poverty, accepting any type of external funding from the state or federal government could annul their tribal sovereignty.

In light of all of the literature that describes opposing insights into level of involvement that principals should have in establishing processes to control resources, as well as the cultural and political forces that may influence administrators’ ability to establish equitable processes and protocols, Howard Merriman, a former superintendent of the Columbus School District in Ohio during the early 1980s, offered this insight into how researchers and school leaders can address the conflicting advice related to how leaders should build systems for technology decision making processes:

Our immediate problem as a school district was to make a decision: to do nothing to control or standardize technology, thereby allowing hardware varieties and software collections to grow on a school-by-school basis; to standardize and allow building-by-building development through localized fund-raising and interests; or to standardize, develop a system plan, aggressively seek financial support for the plan, and implement such a plan. [...] A district-wide plan, however, found support among those who believe that computers could make a difference, [where] everyone, not just math teachers, should have access; all races, socio-economic levels, and boys and girls should have equal access. It was clear that standardization with a plan to implement a system-wide program made sense. Standardization addresses the problems of equity and access. (Merriman, 1986, p. 172, emphasis added)

Faced with a political context of de-facto school segregation because of zoning in the Columbus School District, Merriman (1986) theorized that his urban school district needed to use systems
thinking to implement a system-wide program that standardized the processes that schools used
to access technology resources, rather than only standardizing the type of technology schools had
or the funding streams that schools would use. From this perspective, Merriman (1986) suggests
that establishing systems thinking processes from the standpoint of equity and access could
reorient technology leaders, from the building leaders to policy makers, to become advocates of
educational equality, rather than agents of technological, social, or political pressures.

The literature explicating the intersection of process and resource allocation start by
positioning systems thinking as a key mechanism to encourage democratic decision-making with
technology. However, it is still unclear from the literature outlined in the section above about
who is ultimately responsible for maintaining the system and about how leaders can employ
systems thinking under certain social, political, and technological limitations.

**Outcomes and resource control.** Table 4-1 indicates that 10 studies researched the link
between student access to technology and levels of technology use. Over the last decade, there
have been lingering questions of whether simply providing access to technology improves
student achievement. At the turn of the century when technology started to emerge as a popular
reform effort in schools and districts, a study by Cuban, Kirkpatrick, and Peck (2001) examining
technology use in two schools in Silicon Valley in Northern California concluded that simply
providing access to technology did not lead to any substantial changes in teacher or student
technology use. The literature describes similar results across different demographics and school
types. In a study exploring technology use in schools in the Alaskan Arctic, Subramony (2007)
finds that school administrators reported that improved access to technology did not actually lead
to improved levels of teacher or student technology use. Likewise, research on Catholic schools
echo this sentiment, as researchers found that despite principals reporting little to no issues with
technology access in their schools, Catholic schools with larger proportions of low-income students reported that their teachers were less likely to use technology in meaningful ways within their instructional practice (Gibbs, Dosen, & Guerrero, 2013).

Despite the strong rhetoric about bridging the digital divide in order to improve schools, these findings highlight a few fundamental misconceptions that leaders might have about the link between resource control and student outcomes. Mullen (2011) highlights that these misconceptions tend to start in principal preparation programs, where aspiring school leaders are in courses that emphasize the “technocratic, state-driven priorities for school leaders that highlight finance, management, and testing” instead of helping future leaders establish a “vision for equitable education and a just accountability system for schools” (p. 337). From a technology leadership perspective, principal preparation that focuses on what technology tools to use or what processes to establish is not enough. Understanding how these access and processes related to technology are part of a larger vision for technology integration and digital equity is necessary for school improvement with technology (Anderson & Dexter, 2005).

For in-service school and district leaders, the literature advises that school leaders need more support in implicitly understanding how their technology purchasing supports instructional and curricular improvement efforts, rather than bolster their competitive edge (Blignaut et al., 2010; Newby et al., 2012). Interestingly, in a study on U.S. technology policy implementation examining data from teachers and administrators on the National Assessment of Educational Progress (NAEP) survey, Becker (2006) finds that technology use in schools was higher in states where technology funding was tied to competitive state grants, rather than simply integrated into the state curricular standards. Even schools in developing countries, like Uganda, that struggle to purchase technology, Newby et al. (2012) point out that principals actually enjoy investing
capital into technology not because of its educational benefits, but because technology use in the classroom is a major selling point for parents to enroll their students in their school. Whether explicitly or implicitly, Webster (2017) writes that many leaders have great difficulty with understanding the shortcomings of the notion of technological determinism, or the perspective that technological change inevitably drives outcomes. Webster (2017) adds that this competitive perspective that many school leaders have to “keep up with technology or be left behind” (p. 25) often leads to poor, misinformed decisions, teacher resistance, and wasteful spending, rather than improved teacher or student outcomes. This is even more consequential for leaders in schools within historically disenfranchised communities where decisions to buy technology are often a result of political or social pressures or top-down mandates, instead of the result of the educational goals that teachers and leaders establish within their particular school communities (Bosco, 1986; Webster, 2017). Helping leaders think through these priorities and how the technology aligns to the instructional and achievement goals they want to set students and teachers within their individual communities should one key focus for pre-service leadership preparation and in-service technology professional development (Mullen, 2011).

The literature offers minimal evidence that there is an association between resource control and school outcomes. While some research points to the shortcomings of leadership preparation as one reason for the lack of evidence connecting resource allocation to school outcomes, others note that deeply engrained assumptions that technology leaders have that technology itself will elicit instructional improvement has impeded progress in examining the link between technology resources and positive school outcomes.

**Summary of findings.** These studies as a whole point to the many concerns that many school leaders have about controlling the access, flow, and educational impact of the technology
resources they acquire. Most of the studies speaking to resource control reference material resources, as opposed to human resources. The literature continues to document deep disparities in how leaders access technology resources for their schools in the face of enduring digital divide in countries across the globe, and more prominently, in the United States based on urbanicity, socioeconomic status, race, gender, and ability status. Along with inequitable access, the literature also provides conflicting insights into how leaders can establish effective processes for purchasing technology for their schools, as schools in historically disadvantaged communities often deal with conflicting, top-down mandates from a district or ministry of education, as well as unique cultural or political pressures. Although the literature does not offer strong evidence regarding how principals’ control of resources impacts student or teacher outcomes, there is a need to support pre-service and in-service school and district leaders, particularly in historically underserved communities, in establishing educational goals that mirror the needs of their specific school contexts before making any decisions about acquiring technology-related resources.

Theme 2: Distributed Leadership

Description of theme. The second theme that I found within the body of literature intersecting technology, leadership, and social justice is distributed leadership. One of the most prominent theoretical models within the school and district technology leadership literature base describe technology leadership as a form of distributed leadership, or instructional leadership that is “distributed over leaders, followers, and the school’s situation or context” (Spillane, Halverson, & Diamond, 2004, p. 11). As opposed to early conceptions of instructional leadership that focus exclusively on the principal (Hallinger & Murphy, 1985), distributed leadership rests on the assumption that principals and teachers share the responsibility to perform leadership behaviors that are directly related to instruction (Gronn, 2002; Spillane, Halverson, & Diamond,
Several educational leadership studies have argued using distributed leadership as a guiding theoretical framework helps researchers capture how all stakeholders in a school community – faculty, staff, and administrators – perceive leadership in order to elicit a more robust understanding of leadership practice within their immediate contexts (Goff, Goldring, & Bickman, 2014; Halverson & Kelley, 2017; Halverson, Kelley, & Shaw, 2014; Heck & Hallinger, 2009; Marks & Prinzing, 2003; Urick & Bowers, in press).

Likewise, Dexter (2011) extends this notion of distributed leadership into the conception of technology leadership:

School leadership for technology integration nonetheless provides an excellent opportunity to examine distributed leadership because its outcomes are clearly recognizable in terms of teachers’ learning and use of technology-supported instruction in classrooms. It is nearly always carried out by a team of people, and it has distinct technical, operational, and instructional components. (p. 170)

Mirroring research that argues that effective technology leadership is more of a distributed, shared leadership practice rather than a practice that the principal enacts alone (Haughey, 2006; Rikkerink, Verbeeten, Simons, & Ritzen, 2016), this quote from the Dexter (2011) attempts to push technology leadership research past a simple definition of distributed leadership as delegating leadership tasks toward theorizing how researchers can understand the full scope and impact of technology leadership by using a distributed leadership perspective to explore how all aspects of the school organization embrace technology leadership for school improvement.

However, at the same time, Harris (2004) argues that theoretical and practical applications of distributed leadership sometimes “ignores the major structural, cultural, or micropolitical barriers operating in schools that make distributed forms of leadership difficult to implement” (p. 19). Again, using the Theoharis and Brooks (2012) framework of access, process, and outcomes, I explore how literature intersecting technology, leadership, and social justice
contends with this conceptualization of technology leadership as a distributed leadership practice. My findings discuss several tensions pertaining to how leaders define and access high-quality technology leadership, create operational processes to implement their technology leadership, and share technology leadership responsibilities in a way that impacts student or teacher outcomes.

**Access and distributed leadership.** As outlined in Table 4-1, 15 studies attempted to define the technical role of a technology leader and describe how schools access and retain high-quality technology leaders. In his reflection of his time as an assistant superintendent in Columbus, Ohio, Merriman (1986) recalls a time where principals started to aggressively seek out more microcomputers with help from the parent-teacher association. He proudly recalls how he implemented his new technology plan and advises superintendents that technology implementation efforts “require extraordinary communication efforts” (p. 182) to the technology staff, to the Board of Education, to the teachers and building principals, and to the larger community through the media. This sentiment is mirrored in several other position papers and ethnographies that position the principal as the “navigator” of schools of the future (Leone, Warnimont, & Zimmerman, 2009) or the ultimate “bureaucrat-administrator” for navigating technology leadership in certain urban school contexts (Gooden, 2005). However, Anderson and Dexter (2005) warn that “rapid technical change and highly uneven distribution of expertise make technological leadership particularly challenging – focusing on theories of learning organizations would help to theoretically address how to incorporate culture and community into refined conceptions of technology leadership” (p. 73). Consequently, the ways in which the literature started to define the term technology leader needed to change (Wilmore & Betz, 2000).
In order to sustain high-quality technology leadership, some of the literature looks beyond the role of the principal to understand how individuals in other roles, like teachers, technology coordinators, and even school librarians, function as technology leaders. Several studies note that teachers are crucial to the success of technology leadership efforts in that they work closely with students and are able to assist with technology leadership efforts at the ground level with students, families, and other teachers (Blau & Presser, 2013; Chang et al., 2008; Dexter, 2011). Similarly, technology coordinators and technical support specialists in schools also play a critical role in sharing the responsibility of technology leadership in that they support the instructional program along with ensuring that the infrastructure works properly (Davidson & Olson, 2003; Dexter, 2011). Interestingly, Ennis-Cole and Smith (2011) spoke to the central role that school librarians have in supporting technology leadership, as librarians often help train teachers to use new digital tools, advocate for innovative instructional resources, and buy assistive technologies to aid in differentiating classroom content. In some cases, even students can serve as informal technology leaders to ease the demand on principals, teachers, and the technical support team (Cuban et al., 2001).

On the surface, the literature describes a conceptual shift toward understanding technology leadership as a distributed leadership practice. However, at closer examination, the literature reveals a few negative consequences that distributed leadership can have for formal and informal leaders in schools. Dawson and Rakes (2003) found that principal technology professional development beyond training on how to use certain technology tools can positively influence the principals’ perception of their technology leadership. Despite this fact, access to technology leadership professional development remains inequitable (Schrum et al., 2011). In their study of 214 North Louisiana administrators, Leonard and Leonard (2006) note that many
of the school leaders felt unqualified to be technology leaders and offered that the lack of professional development funds and resources to get training on new technologies contributed to their lack of preparedness to lead for technology in their schools.

Further, even though much of the literature highlights the positive experiences that teachers and administrators have with sharing the technology leadership responsibilities (Blau & Presser, 2013; Chang et al., 2008; Dexter, 2011), Deryakulu and Olkun (2009) report that some teachers in Turkey report very negative experiences, noting that that some principals used their position of power to force them to perform tasks that were outside the bounds of their responsibilities, like repairing personal devices or installing unnecessary software. One Turkish teacher in the Deryakulu and Olkun (2009) study noted that it was often difficult to cultivate the larger instructional vision for technology when “they [administrators] see me as computer fixer or a repairman” (p. 53).

In all, although the definition of technology leadership has evolved to reflect a distributed conception of leadership, the literature intersecting access and distributed leadership suggests that some school contexts do not necessarily have the material or political means to make this conception of technology leadership come to fruition. The literature also notes that even though distributing leadership could yield positive experiences for teacher leaders, leaders in formal positions must be cautious in how they build relationships with informal technology leaders within the organization.

**Process and distributed leadership.** As indicated in Table 4-1, twelve studies discuss the ways in which leaders create organizational processes to distribute their technology leadership responsibilities most effectively. In their case study of one U.S. high school during the first year of an iPad initiative, Hughes, Boklage, and Ok (2016) note that principals described the
way they operationalize their technology leadership as “bottom-up innovation with top-down support” (p. 283). However, in his study on New Hampshire superintendents’ perceptions of the institutional factors that influence teacher technology integration habits, Shuldman (2004) notes that these superintendents distributed their leadership in an operational model on multiple levels that does not necessarily include the “bottom-up,” grassroots efforts of teachers as often described in the technology leadership literature as the ideal way to enact systems thinking and distribute technology leadership efforts (Hughes et al., 2016; Levin & Schrum, 2013, 2014). On the first level, superintendents mention that they prioritize their own involvement in technology leadership, as superintendent involvement sends “a clearly defined and articulated technology message used to build broad community and school board support to secure funding, goodwill and buy-in” (Shuldman, 2004, p. 330). The second level pertains to the involvement of the building principal. The superintendents in the Shuldman (2004) study felt that it was important that principals understand the vision and work with teachers to implement the vision at the school level. Finally, on the third level, Shuldman (2004) notes that “these superintendents all believe that there must be some form of oversight and management of the district’s technology resources and efforts, both technological and instructional” (p. 331), which includes either a technology coordinator or director of technology at the district level. Other studies have also described how district leaders should tap into other school staff, like school counselors (Childers Jr. & Podemski, 1984), as part of their system of technology leadership as counselors are often skilled in supporting the emotional, intellectual, and developmental impact of new technologies on students, teachers, and parents.

Although the superintendents in the Shuldman (2004) study represent a very small subset of district administrators around the U.S., it is surprising that they did not mention teachers as a
part of the institutional processes they establish to create systemic support for their technology leadership, especially as many other studies have included teachers in their definition of a technology leader (Blau & Presser, 2013; Chang et al., 2008; Dexter, 2011; Hughes et al., 2016) and emphasize the importance of transparency with teachers when implementing new technology initiatives (Levin & Schrum, 2014). One study points to constant teacher resistance as a potential barrier to including teachers in certain technology leadership processes (Sincer, 2013). Another study finds that initiatives that focus on instructional innovation in urban schools were more successful when there was a lower level of dependence on others, leading some teachers to dismiss other teachers or principals from engaging in their process for innovating instructional practices (Zhao et al., 2002). Sometimes, teachers are excluded on purpose, as findings from one case study of five schools described how district leaders in an urban district simply decided to handle the entire implementation of a laptop program, including establishing committees, choosing the technology, and offering training without teacher input (Dexter, 2011). Although much of the technology leadership literature positions teachers as a core element in a systems thinking model of technology leadership, school and district administrators appear to entrust other types of technology leaders with specific duties and responsibilities that are more adjacent to classroom teaching roles (Davidson & Olson, 2003). Even though notions of distributed leadership position the perceptions of teachers as a critical component to understanding leadership practice on the ground level, formal technology leaders, especially at the superintendent level, may not see value in involving teachers in every aspect of the decision-making process when it pertains to technology.

Further, only a few studies that examine technology leadership processes through the lens of distributed leadership explicitly mentioned how leaders distributed their technology leadership
through the material resources they purchased. While some studies mention how the principal upgraded the technology infrastructure (Hughes et al., 2016; Levin & Schrum, 2013, 2014) and how district leaders established technology distribution models for students and teachers (Dexter, 2011), others primarily focused how leaders created processes and distributed their leadership through human resources, or individuals in middle management roles that they hired and were directly responsible for supervising in order get the outcomes they desired (Blau & Presser, 2013; Davidson & Olson, 2003; Shulman, 2004). Bowers (1992) argues that this unspoken perspective within the technology leadership literature promotes the notion that the technology itself is “culturally neutral [and] how this myth continues to frame how the power of technology, and the person’s relationship to it, are understood” (p. 21) and that material resources do not necessarily speak to leadership practices within an organization. This paradigm is also reflected in the larger technology leadership research where most of the focus is on how leaders are using the materials, rather than an examination of how the materials reflect leadership vision (Webster, 2017). If distributed leadership, by definition, is leadership that is spread across the day-to-day actions of leaders, as well as the macro-level processes, like resource allocation, the literature has yet to offer many robust studies that ask leaders, in both formal and informal roles, to reflect on the ways that their human and material resources reflect a coherent leadership vision for technology within their school contexts (Webster, 2017).

At the intersection of process and distributed leadership, the literature espouses that technology leadership is a grassroots operation that is supported by many formal and informal leaders throughout all levels of the organization. However, some formal leaders at the helm of leadership at the district level do not necessarily consider teacher input when making decisions about technology. Likewise, if distributed leadership is a function of everyday leadership
behaviors and larger organizational processes, like hiring or resource allocation, the literature does not contend with how leadership is distributed across material resources, reinforcing the myth that technology is neutral and cannot embody cultural norms and values.

**Outcomes and distributed leadership.** As seen in Table 4-1, nine studies offer empirical evidence exploring the extent to which distributed leadership models are associated with positive teacher school outcomes, but only one study associated distributed leadership models with improved student achievement. In describing the association between distributed leadership and teacher outcomes, some studies find that when leaders focus on distributing their technology leadership duties related to transformational leadership behaviors, like collaborating on decision making and developing professional teacher capacity through emotional support, distributed leadership is associated with greater collegiality and collaboration among those implementing new instructional innovations in their classrooms (Afshari, Bakar, Luan, & Siraj, 2012; Pautz & Sadera, 2017; Rikkerink et al., 2016). Other studies highlight the positive effect that distributing instructional leadership responsibilities, like building strong instructional vision and curriculum, to a technology committee or group of teacher leaders has on teachers’ pedagogical effectiveness or levels of involvement in the school or district technology-related reform efforts (Anderson & Dexter, 2005; Blau & Presser, 2013; Blignaut et al., 2010; Davidson & Olson, 2003; Paredes Scribner & Bradley-Devine, 2010). Surprisingly, only one study examined the impact of distributed leadership on student outcomes. Wong and Li (2008) use hierarchical linear modeling to examine survey data from 963 principals, teachers, and technology coordinators in 122 schools in Hong Kong and found that at the teacher level, teachers’ perceived changes in pedagogical practice with technology were associated with perceived changes in student learning, while at the school level, collegiality, which the authors
define as school climate and technology implementation strategies, had a positive impact on perceived changes on student learning. In their conclusion, Wong and Li (2008) offer:

   Educational practitioners need to expand the concept of ICT [technology] implementation for mere ICT use to ICE use in the context of pedagogical and organizational interventions. If school effectiveness, from teacher perspectives, is found to improve in a context of establishing collegiality to foster pedagogical innovations, then school administrators and policy makers should give more attention to both the social contexts and the institutional culture in which teachers are situated. (p. 115)

While the majority of the literature exploring the impact of distributed leadership focus on the individuals who perform technology leadership, like teachers, Wong and Li (2008) challenge researchers to more deeply investigate how distributing technology leadership impacts student achievement mediated through the social and institutional context of where technology leadership occurs.

   The studies exploring outcomes and distributed leadership offer that distributing leadership efforts can positively impact student and teacher outcomes. However, the literature also indicates that it is equally important to consider the context in which leadership is enacted in order to understand how the organizational context influences distributed leadership through human and material resources within an organization.

   **Summary of findings.** These studies related to distributed leadership explore the ways that leaders distribute technology leadership through people and processes to achieve certain outcomes. Most of the studies focus on how leaders distribute their technology leadership through human resources, as opposed to material resources. There is a need for more robust research that deepens the conception of technology leadership as distributed leadership that considers how leadership is distributed across human and material resources to combat the notion that technology is values-neutral. However, in historically underserved schools where
principals feel unprepared to lead or where there are political or monetary limitations, there is a pattern of portraying distributed leadership as a top-down mandate, rather than bottom-up collaboration. While some of the technology leadership studies in this theme offer insight into how distributed leadership model of technology leadership can serve as a tool to improve teacher practice, there is also a need to understand how distributed models of technology leadership impact outcomes, mediated through the larger social and organizational context of schools.

Theme 3: Sociocultural Influences

Description of theme. The last theme that I identified within the body of literature intersecting technology, leadership, and social justice relates to sociocultural influences. A common argument that many proponents of technology integration in schools offer is that technology is a just tool and that supporting teachers and leaders to use these tools more effectively should be the primary focus of researchers, policy makers, and educational leaders (Chapter 2, this volume; Zhao, Alvarez-Torres, Smith, & Tan, 2004). However, technology is not culturally neutral (Bowers, 1992). In fact, Subramony (2017) argues that critical scholars over the last two decades have pushed against this notion, arguing that “technology embodies economic, social, and cultural power […] Technology that has the power to emancipate also has the power to subjugate and oppress” (p. 29). Bradshaw (2017) further adds:

Individuals and educational technology professional organizations are increasingly recognizing the urgent need to understand complex interactions between culture, learning, and technology. With this growing realization, merely replicating what and how educational technology has been practiced in the past is not sufficient. Nor is it adequate to assess the value and appropriateness of current and future efforts according to our own experiences, perceptions, and perspectives. (p. 8)

Specifically for the technology leadership field, Bradshaw (2017)’s assertion about the urgent need to understand the impact of culture on technology leadership practices is even more poignant. Even in light of the vast number of studies that document the growing digital divide
that many leaders grapple in their schools year after year (Gorski, 2002, 2005; Hohlfeld, Ritzhaupt, Barron, & Kemker, 2008; Normore & Lahera, 2018; Ritzhaupt, Liu, Dawson, & Barron, 2013; Valadez & Duran, 2007; Warschauer, 2016; Warschauer, Knobel, & Stone, 2004), recent reviews of the body of technology leadership note that there is a dearth of research studies examining how leaders address cultural and social issues in their technology leadership efforts (Anderson & Dexter, 2005; McLeod & Richardson, 2011; Richardson et al., 2012).

In examining the literature intersecting technology, leadership, and social justice, I borrowed from notions of sociocultural theory outlined in the body of research on computer-assisted learning to define *sociocultural influences* as the mediating historical, social, or cultural forces that change actions, shape perspectives or behaviors, or inform individuals’ perceptions of the world (Warschauer, 2005). Given this definition, the literature within this theme seeks not only to understand how sociocultural influences influence technology leadership, but also to discuss how critical technology leadership can also push against certain sociocultural influences pertaining to accessing quality resources, establishing equitable processes, and achieving desirable technology-related outcomes in schools.

**Access and sociocultural influences.** Table 4-1 notes that a total of 4 studies examined how certain sociocultural influences change how leaders provide access to certain technological resources and opportunities. Wood (1973) was an early advocate for future educational leaders to understand the nuances of human behavioral sciences in order to better communicate with people of different cultural backgrounds. Similarly, as technology emerged as a key communication method in schools and in society at large, Slenning (2000) argued that future school managers must have sociocultural skills to use technology effectively in order to navigate various stakeholders inside and outside the school. Despite this charge, there were only three examples
within the literature that actually offer insight into how school leaders can utilize this deeper understanding of how the sociocultural context of their community impacts issues of technology access inside and outside of school.

Inside of school, Quilling (1999) highlights the need for school leaders to consider how gender bias within the information technology discipline impacts young women and their interest in technology. Quilling (1999) encourages leaders to cultivate a set of educational strategies to ensure gender equity, like purchasing software that is free of gender bias, building technology spaces where young women feel welcomed, integrating technology throughout the curriculum, and consistently auditing these strategies to ensure that school policies reinforce gender equity.

Pertaining to outside of school, in their ethnographic study on computer use of transnational Latinx immigrant families, Sanchez and Salazar (2012) document the challenges that older Latinx youth encounter when they serve as “cultural brokers of technology” (p. 100) for their families. These young people often help their parents with setting up their home Internet access and computers with English-speaking vendors, accessing social services, and translating important documents (Sanchez & Salazar, 2012). Sanchez and Salazar (2012) offer that “it is imperative that administrators and teachers demand more of their campus IT programs because these expectations and exposure to advanced technologies will hopefully gush – and not trickle down – into students’ urban Latino households and communities, where children will again push their families to acquire technology sooner” (p. 11). To address this need within the immigrant Latinx community, school leaders must work to provide increased access to families and also work on clearly communicating these new technology initiatives to families in ways in which they can understand and take action (Sanchez & Salazar, 2012). Overall, although these few studies offer some insight into how leaders can provide more access to technology based on the
specific sociocultural needs of their communities, there are still few examples in the literature exploring how leaders perform strategies, similar to the ones outlined above, in practice.

**Process and sociocultural influences.** Table 4-1 indicates that 5 studies examined values that reinforce certain sociocultural norms and constructs that ultimately impact leadership processes. Bowers (1992) warns that school leaders must fight against the cultural norms that leaders in the educational technology industry seek to control. He argues that technology “does not encode the moral guidelines that have traditionally been part of cultures which have evolved ways of living in sustainable relationships with their environments” (Bowers, 1992, p. 27). Therefore, it is important for school and district leaders to establish organizational processes that consider how new technologies fit within the sociocultural norms and values of the school (Bosco, 1986; Webster, 2017).

However, several studies have documented the new leadership challenges that have emerged because of this disconnect between technology and schooling culture. Bosco (1986) offered early insight into the incongruities of technology use and organizational culture:

> Efforts to make use of computers in significant ways in schools requires invention in as real and as important a way as accomplished by those who invented the machines. Vendors and computer experts who have a deep understanding of the computers, but a casual understanding of schools, cannot be expected to figure out how to use computers in schools. *Teachers and administrators need to accept their role in inventing the new forms required to make the technology work in the social context of schools* […] In many, if not all cases, the improvements that teachers can imagine through the use of computers will challenge existing policies and procedures. (p. 126-127)

There are many examples of what Bosco (1986) predicted. Pertaining to student-level processes, Peck et al. (2011) found that leaders in one U.S. high school struggled with navigating the presence of “youth digital media culture” (p. 46) and establishing policies pertaining to student technology use. Similarly, in their study describing the experiences of several teacher leaders in a
technology-based instructional reform initiative in a small urban school, Paredes Scribner and Bradley-Devine (2010) reveal that many of the leadership actions of the female teachers were disregarded or underutilized due to gendered school cultural norms. The authors attribute the women’s experience to “how the cultural construction of teacher leadership shapes or limits the enactment of leadership practices and may reinforce oppressive patterns of interaction among teachers and between teachers and students by legitimizing leadership acts and not others” (p. 516). Even in developing countries where many schools face similar challenges, Gioko (2013) noted that Kenyan leaders had to be cautious and practice “contextual sensitivity” (p. 162) when introducing new tools and pedagogical practices to teachers and leaders in Kenya in order to ensure that teachers will use technology rather than dismiss it as irrelevant or unnecessary. To this end, Bosco (1986) concludes, “it is still rare to find considerations of policy and procedure which impinge in critical ways on the use of computers” (p. 127).

**Outcomes and sociocultural influences.** Table 4-1 also specifies that three studies discussed how technology leaders can leverage sociocultural norms to impact student and teacher outcomes. In his ethnography of one African-American principal in an urban information technology high school, along with an intent focus on improving instruction, Gooden (2005) noted that the principal embraced the role of an “ethnonhumanist” through commitment, compassion, and confidence in order to “fulfill an important role in operating within this sphere [schools] to bring about changes in the education of African-American children” (p. 642). Likewise, at the classroom level, after interviewing several students from the Inupiat Eskimo community in Alaska, Subramony (2007) notes that leaders in historically disadvantaged communities should encourage students to become producers of technology, learning higher-order skills that will benefit them in school and in the workplace, rather than only passive
consumers of technology. Subramony (2007) concludes, “[…] While equitable and adequate access to technology tools and infrastructure is truly of vital importance, […] any discussion about the socioeconomic and cultural consequences of the digital divide…needs to move beyond just debating issues of access to technology in order to truly capture the ramifications of the digital divide” (p. 66). Similarly, Burnard (2011) also documents the success that various school leaders in the United Kingdom had in using music and technology to boost student engagement through creating learning spaces that valued self-expression, creativity, and cooperative learning and that integrated students’ cultural backgrounds into the music curriculum. In all, these studies encourage leaders to leverage the emancipatory power of technology to empower students to use technology in meaningful ways, helping to eliminate the impact of the cultural and digital divide that affect the life outcomes of students from historically underserved communities.

**Summary of findings.** The studies under this theme discussed the reciprocal influence of sociocultural factors and technology leadership and the extent to which this relationship informs how leaders access technology resources, establish democratizing technology leadership processes, and measure teacher and student technology-related outcomes. All of the studies supported the notion that technology leadership is not culturally neutral. While some studies offered insight into how to tailor leadership specifically to fight against or support certain sociocultural norms, especially related to gender and race, very few studies offered practical strategies for how leaders can learn and use sociocultural awareness to adjust their leadership practice. However, several studies agree that leaders have a moral obligation to cultivate learning environments for students, particularly in historically underserved school contexts, where they are producers of technology, engaging in curriculum that prioritizes cultural relevance and promotes higher-order thinking.
Integrated Model of Technology Leadership for Social Justice

**Summary of findings.** The three themes I identified in the literature exploring technology, leadership, and culturally responsive leadership were: (1) resource control, (2) distributed leadership, and (3) sociocultural influences. Continuing with the synthesis phase of the meta-narrative literature review, I map out the relationships among the three themes within the Theoharis and Brooks (2012) framework of access, process, and outcomes to create a new conceptual framework of technology leadership for social justice in Figure 4-1.

Figure 4-1. Integrated Conceptual Framework of Technology Leadership for Social Justice
As outlined in Figure 4-1, my integrated framework of technology leadership for social justice centers on outcomes. Very few of the studies discussed in the previous section explore how different approaches to technology leadership are associated with particular student, teacher, school, or organizational outcomes within districts or countries. As seen in the arrows pointing out from the center circle, I argue that the literature suggests that sociocultural influences mediate how leaders address technology leadership issues of access and process to elicit the student, teacher, school, or organizational outcomes they desire. The literature also suggests that this sociocultural influence may have explicit or implicit norms based on the school context. There was also limited evidence in the literature that distributed leadership or resource control had any direct influence on technology leadership outcomes. Thus, in Figure 4-1, there are no direct arrows from outcomes to the themes of distributed leadership or resource control. It is important that leaders understand that distributed models of leadership theorize that leadership is “distributed over leaders, followers, and the school situation and context” (Spillane et al., 2004, p. 11). As such, my conceptual model for technology leadership for social justice theorizes that sociocultural factors also mediate the ways in which leaders distribute their technology leadership in providing access to high-quality resources, teaching, and educational opportunities, as well as in establishing collaborative processes for making decisions. I imagine that technology leadership for social justice could guide leaders in distributing their technology leadership efforts through the human or material resources that they provide access to and establish processes for in ways that honor and affirm the sociocultural influences within their school contexts, ultimately impacting technology-related outcomes on all levels of the organization.
Discussion

The purpose of this study was to conduct a comprehensive and systematic review of the literature intersecting technology, leadership, and social justice in order to synthesize the findings into a new integrated framework of technology leadership for social justice. I begin the final stage of the meta-narrative review process, the recommendation stage, by reviewing my findings and providing guidance for further applications of my findings in the technology leadership literature.

In the present study, I have four major findings. First, I have employed the Theoharis and Brooks (2012) equity-oriented instructional leadership framework of access, process, and outcomes in order to examine the body of research that intersects the domains of technology, leadership, and culturally responsive leadership. Second, within this subset of literature, I have identified three major themes across 60 qualitative, quantitative, and conceptual studies. These themes were resource control, distributed leadership, and sociocultural influences. Third, I have organized the findings within each theme using the Theoharis and Brooks (2012) of access, process, and outcomes and have provided detailed descriptions of areas of agreement and tension within the literature. Fourth, I have integrated the relationships between the themes and the Theoharis and Brooks (2012) framework into a single model that offers a new conception of technology leadership for social justice. The present study represents one of the most systematic, comprehensive literature reviews of the technology leadership to date and is one of the first studies to offer a critical perspective on the body of technology leadership research.

The first recommendation from my study is that technology leadership research should utilize frameworks anchored in critical theories of leadership to examine technology leadership practices in schools and districts. My findings point to the fact that most studies examining the
intersection of technology, leadership, and social justice focus on the inequitable distribution of material resources. These findings reflect a broadening conversation on the impact on the digital divide on historically underserved communities and how racial and economic discrimination maintains and perpetuates these disparities (Gorski, 2002, 2005, 2009; Normore & Lahera, 2018; Warschauer, 2016; Warschauer & Matuchniak, 2010). However, given the changing nature of schools and the documented cultural mismatch between students and the educators that serve them (Deschenes, Cuban, & Tyack, 2001), Bradshaw (2017) pushes this concern for social justice further and offers an explanation for how critical theory can elicit deeper equity work in the educational technology domain:

Education happens in broader social contexts and, this, must be considered in light of, and as expressions, consequences, and replicators of issues and dynamics in the broader society […] Criticality is a commitment to digging deeper in order to understand broader connections, roots, and ramifications, for the specific purpose of allowing for the full participation and humanity of all. Therefore, criticality requires attention to the struggles of those at the margins of society, and also requires continual self-examination, self-interrogation, and learning regarding one’s own positionalities and perspectives, as well as reflection and action regarding how benefits and harms related to positionalities are established, influenced, and maintained. (p. 9)

As school and district technology leaders have a professional responsibility to understand how educational technology interacts with the modern context of schooling, there is a need for more research that utilizes more critical theoretical and conceptual lenses not only to understand the explicit and implicit implications of the interaction of technology, leadership, and culture, but also to provide technology leaders with the tools to interrogate their own perceptions of educational (in)equality and how these perceptions influence their leadership behaviors. Existing leadership frameworks, like culturally responsive leadership (Khalifa et al., 2016), offer that mastering this criticality can help school leaders build more positive school communities that encourage teacher commitment and bolster student achievement. I encourage researchers to write
more conceptual articles exploring the application of critical theories of leadership to the technology leadership subfield.

My second recommendation implores technology leadership researchers to use more robust methodologies to explore the impact of technology leadership on school outcomes. My findings indicate that there were the least amount of studies examining the connection between technology leadership and school outcomes, which is surprising given that technology leadership is a close derivative of shared instructional leadership (Marks & Printy, 2003; Printy, Marks, & Bowers, 2009; Robinson, Lloyd, & Rowe, 2008) and leadership for learning (Chapter 3, this volume; Boyce & Bowers, 2018b; Hallinger, 2011; Hallinger & Heck, 2010; Murphy et al., 2007) that both explores the connection between leadership behaviors and student achievement. Furthermore, most of the studies that explore the intersection of technology, leadership, and social justice use case study methods to describe the experiences of school leaders within a single context. While it is equally important to understand the specific contexts in which leaders enact technology leadership, as the interest in generalizable research on technology use and technology leadership in schools and districts continues to grow, I recommend that technology leadership researchers look to use more large-scale data with more robust multilevel and person-centered methodologies to more deeply understand the interaction of teacher and leaders perceptions of technology leadership practice and how these perceptions interact with their school context (Chapter 2, this volume; Chapter 3, this volume; Bowers et al., 2017; Boyce & Bowers, 2018a; Hallinger & Heck, 2011; Heck & Hallinger, 2014; Leithwood & Jantzi, 2008; Leithwood, Patten, & Jantzi, 2010; Urick, 2016b; Urick & Bowers, 2014a; Urick & Bowers, 2014b; Urick & Bowers, in press). In addition to this work with large-scale quantitative data, I call for more longitudinal descriptive research that offers practical insights and deeper
investigations into how leaders tailor their technology leadership efforts to address related to issues of access and process within their school communities over time in order to assess the impact of an explicit focus on equity and social justice on student and teacher outcomes.

My third recommendation centers on university principal preparation programs and how they prepare aspiring leaders to serve as technology leaders in their schools. My findings reflect that fact the digital divide is more complex than ever before, and leaders must be better prepared to address this issue in their schools. As research indicates that the ISTE Standard related to equity and social issues in technology leadership has been understudied (Anderson & Dexter, 2005; McLeod & Richardson, 2011; Richardson et al., 2012), I position my integrated framework of *technology leadership for social justice* as a new framework that instructors in principal preparation programs courses can use to examine classic leadership topics, such as resource allocation, instructional leadership, equity and social justice, from a more contemporary theoretical lens.

**Limitations**

One limitation of my study pertains to the data range I used as criteria for selecting the studies to use in the analysis. My systematic, meta-narrative review attempts to capture the breadth of literature as early as 1945. With the Internet boom of the 1990s, I recognize that the literature might define the term, *technology*, differently, and thereby omit articles from the analysis. However, in keeping with the stages of the meta-narrative review methodology, I considered literature from both before and after the advent of the Internet for inclusion in the study. I encourage further comparative research examining how the definition of technology and technology leadership might have changed over time.
The second limitation is that my meta-narrative review of literature is limited to the intersection of technology, leadership, and social justice. Given the large scale nature of research in school and district technology leadership, this study cannot explain the field as a whole, but rather, it provides a connection between critical theories of literature with the body of technology leadership research.

The third limitation was that my study included studies that contained qualitative, quantitative, or conceptual analyses. My study cannot estimate an effect size or establish causal inference across the studies I analyzed. I encourage more quantitative, meta-analytic work to synthesize the effect of technology leadership across time and school contexts.

Conclusion

School and district technology leadership has emerged as a dynamic and complex leadership practice in the digital age, filled with moments of incredible optimism and sometimes frustrating challenges. Along with these moments, there is also now a moral imperative for technology leaders to be champions of equity and justice so that all students, regardless of their background, can use technology as an emancipatory tool to boost their knowledge, showcase their creativity, and connect with their cultural identities.
References

*Indicates references included in the 60 studies reviewed for this study.


Beytekin, O. F. (2014). High school administrators' perceptions of their technology leadership preparedness. *Educational Research and Reviews, 9*(14), 441-446.


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Appendix 4-A: Summary of Literature Used in Analysis

<table>
<thead>
<tr>
<th>Author and Year, Literature Type</th>
<th>Title of Article</th>
<th>Journal, Publisher</th>
<th>Sample and Analytic Method Used</th>
<th>Key Findings and Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Afshari, M., Bakar, K. A., Luan, W. S., &amp; Siraj, S. (2012)</td>
<td>Factors affecting the transformational leadership role of principals in implementing ICT in schools</td>
<td>The Turkish Online Journal of Educational Technology</td>
<td>Questionnaire to 320 principals in Tehran, Iran; SEM</td>
<td>PD- medium effect on transformational leadership; computer competence - large effect on level of computer use and medium effect on transformational leadership role; computer use - medium effect on transformational leadership. Principals did not meet the optimal level of transformational leadership because of disparity between developed vs. developing countries. Principal training not a requirement in Iran.</td>
</tr>
<tr>
<td>Anderson, R. E. &amp; Dexter, S. (2005)</td>
<td>School technology leadership: Empirical investigation of prevalence and effect</td>
<td>Educational Administration Quarterly</td>
<td>Survey to 866 principals; descriptive methods, correlations, regression analysis</td>
<td>School technology leadership aligned to technology goals, policies, budgets, committees, and structural support; technology leadership and students per computer statistically significant predictors of outcomes (net use, technology integration, student tool); access and per student software expenditures were significant predictors for net use</td>
</tr>
<tr>
<td>Bayer (1984)</td>
<td>The culture of technology or cultural diversity: A survey of the educational philosophies of California school principals</td>
<td>The Clearing House</td>
<td>Survey to random sample of California principals;</td>
<td>Female principals more diversity oriented than male principals who are more technologically-oriented</td>
</tr>
<tr>
<td>Becker, J. D. (2006)</td>
<td>Digital equity in education: A multilevel examination of differences in and relationships between computer access, computer use, and state-level technology policies</td>
<td>Education Policy Analysis Archives</td>
<td>NEAP data from 70,382 students in 3,479 schools across 40 states; hierarchical linear modeling - IV: computer use, computer access, IV: race, urbanicity, credentialing, student standards, PD, funding</td>
<td>4.5% of the variance in computer access is between states, majority of variance remains within states; rural areas and schools with majority African-American students have lower levels of computer access; 15.4% of the variance in computer use is between the schools; no different in computer use between low-income boys and girls; Latino/a and African-American students are more likely to use than White students; students in schools with higher percentage of AA student use computers more often. Computer use is likely to be higher in school were computers are available all the time, in labs, and in schools with higher percentages of AA students. Computer use is likely to be lower in rural areas. Computer use is likely higher in states where pre-service teachers have to meet tech requirements and states that earmark funds for tech.</td>
</tr>
<tr>
<td>Blau &amp; Presser (2013)</td>
<td>e-Leadership of school principals: Increasing school effectiveness by a school data management system</td>
<td>British Journal of Educational Technology</td>
<td>Semi-structured interviews with eight secondary school principals, Ministry of Education official, and director of school principals training program in Israel</td>
<td>System provides extensive support for school principals in managing the organization, delegating responsibilities and promoting e-leadership by teaching staff and, consequently, increases the pedagogical effectiveness of their school. e-Leadership through the school management system changes the entire school culture.</td>
</tr>
<tr>
<td>Blignaut, Hinostroza, Els, &amp; Brun (2010)</td>
<td>ICT in education policy and practice in developing countries: South Africa and Chile compared through SITES 2006</td>
<td>Computers &amp; Education</td>
<td>Principals, teachers, and students in schools in Chile and South Africa; SITES 2006 questionnaire</td>
<td>Similar disparities between both countries (related to ICT equipment provision and teachers professional development programs)</td>
</tr>
<tr>
<td>Author and Year, Literature Type</td>
<td>Title of Article</td>
<td>Journal, Publisher</td>
<td>Sample and Analytic Method Used</td>
<td>Key Findings and Results</td>
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<tr>
<td>Bosco (1986) Peer-reviewed article</td>
<td>The organization of schools and the use of computers to improve schooling</td>
<td>Peabody Journal of Education</td>
<td>Autoethnography; position piece</td>
<td>Understanding how the organizational structure of schools influence technology use at the school and district levels; refers to technology and education as a decoupled structure where schools must deal with the conservative structure of schools before considering how computers can impact education</td>
</tr>
<tr>
<td>Bowers, C. A. (1992) Peer-reviewed article</td>
<td>Technology, culture, and the challenge of educational leadership</td>
<td>Teaching Education</td>
<td>Opinion piece</td>
<td>Educational leadership must understand that technology is not neutral and can perpetuate certain values that work against the moral obligation of school leadership</td>
</tr>
<tr>
<td>Brown, B, &amp; Jacobson, M. (2016) Peer-reviewed article</td>
<td>Principals’ technology leadership: How a conceptual framework shaped a mixed method study</td>
<td>Journal of School Leadership</td>
<td>Survey with 39 educators in three school jurisdictions in Alberta, Canada</td>
<td>Principals rated relationship building as one of the highest competences in their performance, while the larger societal context was one of the lowest competences</td>
</tr>
<tr>
<td>Burnard, P. (2012) Peer-reviewed article</td>
<td>Educational leadership, musical creativities, and digital technology in education</td>
<td>Journal of Music, Technology, and Education</td>
<td>Narrative qualitative research</td>
<td>Musical creativity fostered through technology; leaders in education have power to influence school culture and promote diversity in musical creativities and technology</td>
</tr>
<tr>
<td>Chang, I-H., Chin, J. M., &amp; Hsu, C-M. (2008) Peer-reviewed article</td>
<td>Teachers' perceptions of the dimensions and implementation of technology leadership of principals in Taiwanese elementary schools</td>
<td>Journal of Educational Technology &amp; Society</td>
<td>Questionnaire from 1028 teachers from 128 Taiwanese elementary schools; structural equation modeling</td>
<td>Vision, planning, management, staff development, technology and infrastructure support, and evaluation and research are dimensions that explain effective technology leadership; teacher describe budget shortage problems, technology facility problems, staff development problems, and leadership problems as principal's role</td>
</tr>
<tr>
<td>Childers &amp; Podemski (1984) Peer-reviewed article</td>
<td>Removing the barriers to the adoption of microcomputer technology by school counselors</td>
<td>The School Counselor</td>
<td>Delphi study and content analysis with survey data; 41 participants in round one, 49 participants in round 2, and 41 participants in round 3</td>
<td>Counselors can be an important informal leader in supporting principals with technology by supporting the emotional, intellectual, and social consequences, whether positive or negative, that computers will have on students in school</td>
</tr>
<tr>
<td>Clark, K. (2006) Peer-reviewed article</td>
<td>Practices for the use of technology in high schools: A Delphi study</td>
<td>Journal of Technology and Teacher Education</td>
<td>Delphi study and content analysis with survey data; 41 participants in round one, 49 participants in round 2, and 41 participants in round 3</td>
<td>Most important leadership issues pertaining to technology use in schools: (1) community connection and support, (2) access, (3) research and policy, (4) professional development, (5) curriculum, (6) school culture</td>
</tr>
<tr>
<td>Cuban, L., Kirkpatrick, H., &amp; Peck, C. (2001) Peer-reviewed article</td>
<td>High access and low use of technologies in high school classrooms: Explaining an apparent paradox</td>
<td>American Educational Research Journal</td>
<td>21 teachers and administrators, 26 students; qualitative interviews</td>
<td>Schools with &quot;no digital divide&quot; - 4/13 (31%) teachers modified classroom with technology and moved from teacher to student-centered; no time to evaluate technology and computer training was seldom offered; historical legacy, time; defects in the technology</td>
</tr>
<tr>
<td>Davidson, J. &amp; Olsen, M. (2003) Peer-reviewed article</td>
<td>School leadership in networked schools: Deciphering the impact of large technical systems on education</td>
<td>International Journal of Leadership in Education</td>
<td>Longitudinal study (3 years) student in one school district; qualitative interviews, observations, photographs/drawings, reflective journals</td>
<td>Technology integration leadership roles distributed within school (emergence of new roles, repurposing of old roles, creation of new bodies or collective roles); redistribution of leadership roles and greater interdependence of leadership roles; ETS (educational technologists and ATs (administrative technologists); principals primary responsibility was translating technology goals of the school to the local community; hiring staff; approached outside consultants for information on new technology tools</td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th>Author and Year, Literature Type</th>
<th>Title of Article</th>
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<th>Sample and Analytic Method Used</th>
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</thead>
<tbody>
<tr>
<td>Dawson, C. &amp; Rakes, G. C. (2003)</td>
<td>The influence of principals' technology training on the integration of technology into schools</td>
<td>Journal of Research on Technology in Education</td>
<td>Descriptive study; ANOVA</td>
<td>Significant different in principal age in level of school technology integration; Types of training principals received varied across school levels and school SES</td>
</tr>
<tr>
<td>Deryakulu, D., &amp; Olkun, S. (2009)</td>
<td>Technology leadership and supervision: An analysis based on Turkish computer teachers' professional memories</td>
<td>Technology, Pedagogy, and Education</td>
<td>Questionnaires to 74 computer teachers in Turkey; content analysis</td>
<td>Teachers recall unsupportive attitudes, lack of computer skills, lack of administrative skills, lack of expertise in supervision, lack of pedagogical content knowledge</td>
</tr>
<tr>
<td>Dexter, S. (2011)</td>
<td>School technology leadership: Artifacts in systems of practice</td>
<td>Journal of School Leadership</td>
<td>Five schools; qualitative interviews and observations with students, teachers, and administrators in cross-case analysis</td>
<td>Leadership team similar across five schools to have instant access for students; access to technology through laptop distribution patterns - budget constraints at all five schools did not have 1-1 program but constant access; cross-case analysis; staffing to provide support; learning opportunities for technology integration; means for teacher sharing and input</td>
</tr>
<tr>
<td>Dosen, A. J., Gibbs, M. G., Guerrero, R., McDevitt, P. (2004)</td>
<td>Technology in nonsectarian and religious private schools</td>
<td>Journal of Research on Christian Education</td>
<td>Survey with a representative sample of private school principals in Illinois; qualitative analysis</td>
<td>Schools had minimal differences pertaining to technology access between nonsectarian and sectarian schools; most principals report that teachers use technology in minimal ways in the classroom</td>
</tr>
<tr>
<td>Dyal, A., Carpenter, L. B., &amp; Wright, J. V. (2009)</td>
<td>Assistive technology; What every school leader should know</td>
<td>Education</td>
<td>Opinion piece</td>
<td>School leaders must understand the laws and rights of special education students in order to provide access to assistive technologies that aid with learning</td>
</tr>
<tr>
<td>Ennis-Cole, D. &amp; Smith, D. (2011)</td>
<td>Assistive technology and autism: Expanding the technology leadership role of the school librarian</td>
<td>School Libraries Worldwide (chi-square test)</td>
<td>Questionnaire to 508 school librarians; qualitative and quantitative analysis</td>
<td>Librarians felt comfortable with assisting students with autism; librarians use computers to reach out to students; school librarians as AT trainers</td>
</tr>
<tr>
<td>Flanagan, L. &amp; Jacobsen, M. (2003)</td>
<td>Technology leadership for the twenty-first century principal</td>
<td>Journal of Educational Administration</td>
<td>Opinion piece</td>
<td>Find common themes associated with effective technology leadership in schools: (1) student engagement, (2) shared vision, (3) equity of access, (4) professional development, (5) ubiquitous networks; Barriers to technology leadership include: (1) changes in learning experiences, (2) teacher roles, (3) curriculum, (4) organizational leadership and structure, (5) governance and funding</td>
</tr>
<tr>
<td>Garland, V. E. (2010)</td>
<td>Emerging technology trends and ethical practices for the school principal</td>
<td>Journal of Educational Technology Systems</td>
<td>Opinion piece</td>
<td>Principals must contend with the consequences of the digital divide in providing access to technology; principals must also deal with emergent legal issues, like cell phone policies, online safety, fair use and copyright, and other moral and ethical concerns, such as environmentalism, health issues, etc.</td>
</tr>
<tr>
<td>Gerard, L., Bowyer, J. B., &amp; Linn, M. C. (2008)</td>
<td>Principal leadership for technology-enhanced learning in science</td>
<td>Journal of Science and Educational Technology</td>
<td>Qualitative preliminary interviews, content analysis, and design interviews plus a leadership workshop for 13 principals from California, North Carolina, Virginia, and Massachusetts</td>
<td>Principals considered that leadership, curriculum, policy, teacher learning, student outcomes, and financial resources impacted their leadership for technology-infused science curricula; principals ideas around the curriculum were shaped by individual school cultures and politics from the outside</td>
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<tr>
<td>Author and Year, Literature Type</td>
<td>Title of Article</td>
<td>Journal, Publisher</td>
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<tr>
<td>Gibbs, M. G., Dosen, A. J., &amp; Guerrero, R. B. (2013) Peer-reviewed article</td>
<td>Technology in Catholic schools: Are schools using the technology they have?</td>
<td>Catholic Education</td>
<td>Questionnaire to 319 K-12 Catholic principals in 240 schools; chi-square tests</td>
<td>Need to develop leaders personal computer and technology skills before engaging in deeper professional development; set up professional learning communities in order to learn different technologies that are useful for school administration; need to consider school context before implementing solution to technology in schools in Kenya</td>
</tr>
<tr>
<td>Goldman, Semmel, Cosden, Gerber, &amp; Semmel (1987) Peer-reviewed article</td>
<td>Special education administrators’ policies and practices on microcomputer acquisition, allocation, and access for mildly handicapped children: Interfaces with regular education</td>
<td>Exceptional Children</td>
<td>Survey of 33 special education administrators in Southern California</td>
<td>Describes principal’s role as a bureaucrat-administrator and an ethnohumanist; helped school develop goals, conducted energy harnessing to ensure full buy-in of students and teachers, facilitated clear communication, and managed instruction with high expectations but high support; as an ethnohumanist, demonstrated commitment to the education of African-American youth, compassion for families, and confidence in building supportive environment for students and teachers</td>
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<tr>
<td>Gooden, M. (2005) Peer-reviewed article</td>
<td>The role of an African-American principal in an urban information technology high school</td>
<td>Educational Administration Quarterly</td>
<td>Ethnography of one African-American male principal; researcher observations and interviews</td>
<td>85% of rural districts have used distance education; funding, lack of district support, not needed for curriculum requirements (district), difficulty in implementation, personnel, and lack of technology were barriers</td>
</tr>
<tr>
<td>Hannum, W. H., Irvin, M. J., Banks, J. B., &amp; Farmer, T. W. (2009) Peer-reviewed article</td>
<td>Distance education use in rural schools</td>
<td>Journal of Research in Rural Education</td>
<td>Random sample of 417 school districts; descriptives and chi-square tests</td>
<td>School’s cultural norms sometimes undermined principal’s ability to set vision, provide professional learning, and ensure that the organization was prepared with staffing and infrastructure for iPad initiative</td>
</tr>
<tr>
<td>Hughes, J. E., Boklage, A., Ok, M. W. (2016) Peer-reviewed article</td>
<td>A case study of technology leadership in situ: A high school iPad learning initiative</td>
<td>Journal of School Leadership</td>
<td>Case study of first year of iPad initiative at socioeconomically advantaged high school; qualitative interviews and observations</td>
<td>Teachers and leaders play a role in establishing supportive schools cultures that have to grapple with conflicting cultural values of technology</td>
</tr>
<tr>
<td>Jackson, G. A., &amp; Deal, T. E. (1985) Peer-reviewed article</td>
<td>Technology, learning environments, and tomorrow’s schools</td>
<td>Peabody Journal of Education</td>
<td>Opinion piece; case studies of districts</td>
<td>Teachers and leaders play a role in establishing supportive schools cultures that have to grapple with conflicting cultural values of technology</td>
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<td>Author and Year, Literature Type</td>
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<tr>
<td>Peer-reviewed article</td>
<td>Leadership for technology integration: Computing the reality</td>
<td>Alberta Journal of Educational Research</td>
<td>249 administrators in 149 Louisiana schools; descriptive and qualitative analysis</td>
<td>96% of school administrators indicated that technology integration was a school goal; complained about opportunities for professional development, technical maintenance; Only half (50%) of principals indicated that the district had provided funding for technology and teachers complained of access to software (36%). 70% of administrators noted that rural schools had more problems with integrating technology. 56% of principals felt their teachers did not understand the principles of technology integration. 56% note they help qualified to provide technology leadership in their school. 87% wanted to learn more about becoming instructional leaders for technology.</td>
</tr>
<tr>
<td>Peer-reviewed article</td>
<td>New roles for principals of the future</td>
<td>American Secondary Education</td>
<td>Opinion piece</td>
<td>Principals must contend with diverse schools and provide cultures that celebrate diversity, principal as “navigator” for embracing changes in schools.</td>
</tr>
<tr>
<td>Peer-reviewed article</td>
<td>Using systems thinking to leverage technology for school improvement: It’s just not that simple!</td>
<td>Journal of School Leadership</td>
<td>Cross-case analysis of eight award winning schools and districts; qualitative interviews, focus groups, observations</td>
<td>Eight factors for school change with technology: vision to guide teachers in implementing technology in meaningful ways, distributed leadership to ensure that multiple stakeholders have buy-in, technology planning and support from technology staff in implementing technology initiatives, supportive culture where teachers can take pedagogical risks, professional development, curriculum and instructional practices, adequate funding through creative means, and partnerships with local businesses and organizations.</td>
</tr>
<tr>
<td>Peer-reviewed article</td>
<td>Lessons learned from secondary schools using technology for school improvement: it’s not that simple!</td>
<td>Journal of School Leadership</td>
<td>Cross-case analysis of eight award winning schools and districts; qualitative interviews, focus groups, observations</td>
<td>Eight factors for school change with technology: vision to guide teachers in implementing technology in meaningful ways, distributed leadership to ensure that multiple stakeholders have buy-in, technology planning and support from technology staff in implementing technology initiatives, supportive culture where teachers can take pedagogical risks, professional development, curriculum and instructional practices, adequate funding through creative means, and partnerships with local businesses and organizations.</td>
</tr>
<tr>
<td>Peer-reviewed article</td>
<td>The World Wide Web and school culture</td>
<td>Computers in the Schools</td>
<td>Opinion piece</td>
<td>Schools can suffer from cultural lag where the outside innovation is not adopted at the same rate inside of schools.</td>
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<tr>
<td>Peer-reviewed article</td>
<td>Managing technology integration into schools: A South African perspective</td>
<td>Journal of Educational Administration</td>
<td>Survey to 52 South African principals; descriptive analysis</td>
<td>46% of schools had computers in schools for administrative purposes, while 81% had no computers for teaching and learning. Principals viewed access to computers as very important on the survey. &quot;It is the task of the principal to create a motivational climate&quot;</td>
</tr>
<tr>
<td>Peer-reviewed article</td>
<td>An administrator’s perspective of technology in the schools</td>
<td>Peabody Journal of Education</td>
<td>Autoethnography; opinion piece</td>
<td>Describes process for placing technology in schools in the Columbus school district; calls for equitable distribution of technology and clear communication to constituents, especially from the superintendent who ultimately leads the technology initiatives.</td>
</tr>
<tr>
<td>Author and Year, Literature Type</td>
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<tr>
<td>Mullen, C. (2010)</td>
<td>21st Century priorities for leadership education and prospective school leaders</td>
<td>Scholar-Practitioner Quarterly</td>
<td>Opinion piece</td>
<td>Principal preparation programs and professional development programs must do a better job of preparing principals beyond the technical and financial obligations of leadership; must focus on how technologies support human dignity and how to create schools build vision and propt social justice</td>
</tr>
<tr>
<td>Nance (2003)</td>
<td>Public school administrators and technology policy making</td>
<td>Educational Administration Quarterly</td>
<td>256 principals in midwest U.S.; hierarchical ordinary least squares regression</td>
<td>Administrators involvement in technology policy at the building level is high; strongest predictor of leadership was desire to play role and confidence; elementary principals are less likely to be involved in technology policy; urban principals are less likely to be involved in technology policy within their district. A principa's confidence in her or his knowledge and understanding is positively associated with her or his actual level of involvement in technology policy</td>
</tr>
<tr>
<td>Newby, L., Hite, J., Hite, S., Mugimu, C. (2013)</td>
<td>Technology and education: ICT in Ugandan secondary schools</td>
<td>Education and Information Technologies</td>
<td>11 secondary schools in Uganda; qualitative</td>
<td>Schools had limited resources, but principals were investing in ICT. Teacher usage of ICT can be organized in administrative, entertainment, and pedagogical. Administrators use ICTs to attract students.</td>
</tr>
<tr>
<td>Paredes Scribner, S. M., &amp; Bradley-Devine, J. (2010)</td>
<td>The meaning(s) of teacher leadership in urban high school reform</td>
<td>Educational Administration Quarterly</td>
<td>Interpretative case study of seven teacher leaders in urban school district</td>
<td>Many of the female teacher leaders were underutilized in the technology-focused school reform due to covert cultural norms around who was considered to be a leader</td>
</tr>
<tr>
<td>Pautz, S., &amp; Sadera, W. A. (2017)</td>
<td>Leadership practices in a one-to-one computing initiative: Principals’ experiences in a technology driven, second-order change</td>
<td>Computers in the Schools</td>
<td>Phenomenological study of eight elementary school principals in a diverse district; qualitative interviewing and journals</td>
<td>Principals worked as &quot;optimizers&quot; and change agents maintaining responsibility for resources and for morale; provided professional development through learning communities; leveraged partnerships</td>
</tr>
<tr>
<td>Peck, C., Mullen, C. A., Lashley, C., Eldridge, J. A. (2011)</td>
<td>School leadership and technology challenges: Lessons from a new American high school</td>
<td>AASA Journal of Scholarship &amp; Practice</td>
<td>One high school in Southeastern U.S.; qualitative case study</td>
<td>Administrators noted three technology-related challenges: support, teachers &quot;policing&quot; student use versus the need to use it; and &quot;digital media culture that enhanced students' ability to context established authority systems and classroom norms&quot;</td>
</tr>
<tr>
<td>Quilling, J. I. (1999)</td>
<td>Gender, technology, and leadership development</td>
<td>Journal of Family and Consumer Sciences</td>
<td>Conceptual article</td>
<td>Principals must ensure that technology is free of gender bias and must ensure that computer labs and curricular opportunities provide equal opportunity for young women to engage in technology</td>
</tr>
<tr>
<td>Rabah, J. (2015)</td>
<td>Benefits and challenges of information and communication technologies (ICT) integration in Quebec English schools</td>
<td>The Turkish Online Journal of Educational Technology</td>
<td>Qualitative focus groups</td>
<td>Higher student engagement levels, glocalization of the 21st century education and enhancement of the learning process as the main benefits of integrating ICT in English Quebec Schools; lack of supporting school leadership, inconsistent investments in ICT equipment, infrastructure and resources, inflexibility of funding, the need for additional professional development and support and incorporation of technology in evaluations and curricular plans.</td>
</tr>
<tr>
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<tr>
<td>Razzak, N. (2013) Peer-reviewed article</td>
<td>Challenges facing school leadership in promoting ICT integration in instruction in the public schools of Bahrain</td>
<td>Education and Information Technologies Qualitative interviews</td>
<td>Assistant principals mixed about participant perceptions of quality of technology tools and resources; challenges described by APs include, teachers' heavy teaching workload and increased responsibilities that prevent them from finding sufficient time to plan for and start implementing ICT-integrated lessons; lack of knowledge and skills on how to integrate ICT with instruction; technological resources being available only in a limited number of classrooms; having only a small number of computer labs in each school in which ICT-integrated lessons could be held; frequent technical problems with the computer networks and insufficient of technical support specialists available to fix them; insufficient budgeting allocated for ICT resources; and insufficient authority given to the school leadership in setting the ICT-related direction of the school.</td>
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<tr>
<td>Richardson, J. &amp; McLeod, S. (2011) Peer-reviewed article</td>
<td>Technology leadership in Native American schools</td>
<td>Journal of Research in Rural Education 13 principals in Native American schools; qualitative case study</td>
<td>Challenges to technology leadership include un receptive staff and faculty, lack of technology coordinators, isolation and poverty (conflict between state funding and tribal sovereignty)</td>
<td></td>
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<tr>
<td>Rikkerink, M., Verbeeten, H., Simons, R-J., Ritzen, H. (2016) Peer-reviewed article</td>
<td>A new model of educational innovation: Exploring the nexus of organizational learning, distributed leadership, and digital technologies</td>
<td>Journal of Educational Change Three teachers, a principal, and 2 department leaders in Dutch schools; qualitative interviews, policy documents, personal communications, meetings</td>
<td>Learning house model encourages &quot;context-conscious leadership, organizational leadership, and distributed leadership&quot;; reciprocal influence of context on school leaders and teachers pertaining to technology innovations; innovation and distributed leader was necessary at beginning</td>
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<tr>
<td>Sánchez, P., &amp; Salazar, M. (2012) Peer-reviewed article</td>
<td>Transnational computer use in urban Latino immigrant communities: Implications for schooling</td>
<td>Urban Education Three Latina youth, families, and immigrant networks; qualitative - ethnography</td>
<td>Technology at home - youth as cultural brokers; effects of the digital divide - &quot;perpetuates inequities for working-class groups who neither can afford not have access technology&quot;; communication across borders</td>
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<tr>
<td>Schrum, L., Galizio, L. M., &amp; Ledesma, P. (2011) Peer-reviewed article</td>
<td>Educational leadership and technology integration: An investigating into preparation, experiences, and roles</td>
<td>Journal of School Leadership 137 education leadership programs; document analysis, 48 administrators; qualitative interviews</td>
<td>All states, except 2, are not explicit in requiring administrators to have knowledge of technology; Principals report not having formal course; feel responsible for leadership</td>
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<tr>
<td>Shuldman, M. (2004) Peer-reviewed article</td>
<td>Superintendent conceptions of institutional conditions that impact teacher technology integration</td>
<td>Journal of Research on Education Three superintendents; qualitative case studies</td>
<td>For technology, superintendents believe in three levels of leadership are essential for technology integration: their own, principal and technology infrastructure leadership; knowledge and skills; time; external conditions that impede: teachers' technology capacity, and it's easier to fund computer labs and hire technology teachers</td>
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<tr>
<td>Sincer, M. (2013) Peer-reviewed article</td>
<td>Challenges school principals facing in the context of technology leadership</td>
<td>Educational Sciences: Theory &amp; Practice Qualitative interviews of six elementary principals in Turkey</td>
<td>Challenges for tech leadership include bureaucracy, lack of resources, resistance to innovation, lack of in-service training, and poverty</td>
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<tr>
<td>Slennings, K. (2000) Peer-reviewed article</td>
<td>The future school manager: Information and communication technology aspects</td>
<td>Education Media International Conceptual article</td>
<td>The future school manager must have sociocultural skills to manage individual and groups and use technology in a way that is aligned to the sociocultural norms and changes in society and in schools</td>
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<tr>
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<td>Subramony, D. P. (2013)</td>
<td>Understanding the complex dimensions of the digital divide: Lessons learned in the Alaskan Arctic</td>
<td>Journal of Negro Education</td>
<td>Ethnographic case study of principals, students, and teachers among the Inupiat Eskimo; qualitative interviewing and observation</td>
<td>High comfort with technology but needed to encourage students to become producers instead of only consumers of technology in order to combat social barriers that impede success for this particular community</td>
</tr>
<tr>
<td>Webster, M. D. (2017)</td>
<td>Philosophy of technology assumptions in educational technology leadership</td>
<td>Educational Technology and Society</td>
<td>Qualitative, descriptive study with grounded theory methods</td>
<td>Three technological assumptions for K-12 technology leaders: (1) technology change is inevitable, (2) keep up with technology or be left behind, and (3) educational goals should drive the curriculum. Philosophies related to technological determinism could lead to poor decision making and technology that is disconnected to larger educational goals</td>
</tr>
<tr>
<td>Wilmore, D., &amp; Betz, M. (2000)</td>
<td>Information technology and schools: The principal’s role</td>
<td>Journal of Educational Technology and Society</td>
<td>Conceptual paper</td>
<td>Structure of leadership for technology has changed and must align to schools. Change management and leadership are necessary to elicit lasting change</td>
</tr>
<tr>
<td>Wong, E. M. L., &amp; Li, S. C. (2008)</td>
<td>Framing ICT implementation in a context of educational change: A multilevel analysis</td>
<td>School Effectiveness &amp; School Improvement</td>
<td>1,076 teachers from 130 schools in Hong Kong; hierarchical linear modeling</td>
<td>Perceived changes in student learning was substantially higher for teachers with a better perception of the collegial capacity of ICT implementation strategies; school mean for perceived changes in student learning was higher in school with teachers experiences greater changes in pedagogical practice; a more cohesive school climate and better government ICT policy raised the mean for perceived changes in student learning.</td>
</tr>
<tr>
<td>Wood, C. (1973)</td>
<td>The education of the principal, continuous and changing</td>
<td>American Secondary Education</td>
<td>Opinion piece</td>
<td>Principal of the future must use system design with technology and employ diverse faculty in order to meet the demands of changing school cultures.</td>
</tr>
<tr>
<td>Zhao, Y., Pugh, K., Sheldon, S., Byers, J. L. (2002)</td>
<td>Conditions for classroom technology innovations</td>
<td>Teachers College Record</td>
<td>10 teacher teams; qualitative interviews, observations, and surveys</td>
<td>11 conditions for classroom innovation: knowledge of technology, pedagogy-technology compatibility, knowledge of organizational and social culture, distance from school, resources, and current practices, technological infrastructure, human staff, organizational culture</td>
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### Appendix 4-B: Summary Table of Studies by Theme


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<th>Themes</th>
<th>Access</th>
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<td>Razzak (2015)</td>
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<td>Peck, et al. (2011)</td>
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