2021

THE LANDSCAPE OF PERSONALIZED LEARNING IN LONG ISLAND, NEW YORK

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LONG ISLAND, NEW YORK

A dissertation submitted in partial fulfillment
of the requirements for the degree of

DOCTOR OF EDUCATION

to the faculty of the

DEPARTMENT OF ADMINISTRATIVE AND INSTRUCTIONAL LEADERSHIP

of

THE SCHOOL OF EDUCATION

at

ST. JOHN'S UNIVERSITY
New York
by
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Date Submitted 4/19/21

Date Approved 5/19/21

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ABSTRACT

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Janna Pistiner Ostroff

The study explored the variation in personalized learning within and between Long Island districts. Timely insight into the relationships between technology resources and personalized learning can inform critical fiscal investments throughout the COVID-19 global pandemic and beyond. An electronic survey based on a 2017 RAND Corporation study was sent to teachers in five districts to measure their use of indicators of personalized learning. This study examined relationship between personalized learning and its subcomponents and technology support variables, including 1:1 student device access, home and school internet access, learning management system adoption, and per student dedicated technology staff. While there were large differences in student device and internet access between districts observed, the results indicated that most of the variance in personalized learning was among teachers, not districts, and is largely unrelated to district-level factors.

ACKNOWLEDGEMENTS

First, I want to thank the faculty at St. John’s for their guidance throughout this doctoral program. I feel lucky to be mentored by the brilliant Dr. Erin Fahle, who provided insightful feedback that enabled me to continually learn and grow throughout this process. I am grateful to Dr. Anthony Annunziato and Dr. Stephen Kotok for serving on my committee to review my work. My cohort at St. John’s provided me with a supportive team of educational leader friends with whom I enjoyed learning. A huge thank you to my dissertation partner Dr. Lauren Porter for guiding me back to my work when I needed it most!

Thank you to my colleagues for encouraging me to undertake and complete this challenge. I have the unique pleasure of working with an inspiring K-12 Science and Technology Department at Oyster Bay Schools. I also feel grateful for the support of my current and former Superintendents; Dr. Laura Seinfeld and Dr. Francesco Ianni. I owe a special thank you to Assistant Superintendent Dr. Lisa Mulhall for her mentorship throughout my learning at Oyster Bay-East Norwich Schools. My dissertation work was enriched by precious current and former Oyster Bay thought partners, Dr. Ryan O’Hara, Dr. Joseph Pequiera, Sabrina Meehan, Dr. Lara Gonzalez, Dr. Timothy McCarthy, Dr. Valerie Vacchio, Tami McElwee, Sharon Lasher, Kevin Trentowski, Dr. Marisa Bel, Jack Bixhorn, and (soon to be Dr.) Jack Burke.

Thank you to my dream tech team Bryan Dracker, Brian Rosado, and Jalen Perkins for the hard work, collaborative spirit, and ingenuity they bring to all they do for our community. It is unique to find a clerical team and business office that place students at the center of all they do. I feel grateful to work with Michael Cipriani, Christine Kim, Rita Bizzaro, Cathleen Petrone, Darlene Dolan, and countless others who do all they can to support students.

Thank you also to my NASTECH and LISTEMELA colleagues who support my continued work on behalf of teachers and students. A huge thank you to the assistant superintendents and technology directors throughout Long Island who helped me conduct my study. Your kindness and generosity during difficult times was appreciated.

I am forever grateful to my parents Felipe and Donna Pistiner, for all they have sacrificed and given me. They model life-long learning, integrity, generosity, and kindness in all that they do. To my Plainview village, thank you for the carpools, the encouragement, and the joy, without which I could not have managed this feat! Thank you to my girlfriends who motivate me, laugh with me, and always root for me.

Most importantly, I need to thank my husband, Adam. You meet every new challenge with positivity. Having you beside me makes me stronger and more courageous. Thank you for being my partner on this wild ride and always telling me to go for it.

To my beautiful boys Jack and Henry, thank you for your support and respect for my work and goals. While this program certainly infringed on some of our treasured time together, I watched you mature and become increasingly independent while I worked. I am so proud of you and excited to have more time for fun!

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CHAPTER 1

Introduction

Personalized learning is “a progressively student-driven model in which students deeply engage in meaningful, authentic, and rigorous challenges to demonstrate desired outcomes” (Kallick & Zmuda, 2017). Within the classroom, personalized learning can be observed in students’ voice, co-creation of learning goals and assessments, social construction of ideas with others in a learning community, and self-discovery or reflection (Kallick & Zmuda, 2017). To empower students with the resourcefulness, flexibility, and creativity to succeed in an ever-changing global world, the fields of education are shifting away from prescriptive teacher-centered practices towards personalized learning (Zhao, 2012).

“Personalized learning” has therefore become a central goal of federal and state policy documents and inextricably linked with technology. The National Education Technology Plan (NETP) includes the term “personalized learning” 34 times (United States Department of Education, 2017), stating that technology can enable learning experiences that are more engaging and relevant (United States Department of Education, 2017, p. 9). New technologies also enable teachers to design more efficient personalized learning experiences for classes of students. For example, internet access to large libraries of resources, responsive competency-based software, tools for ongoing self, peer, and teacher feedback better enable student voice and ownership of classroom content, goals, and assessment. Videoconferencing, virtual interactive tours, and live streaming offer student participation in limitless opportunities for self-discovery or reflection on learning and how it applies to life.

Toward the implementation of "personalized learning," the U.S. education system has invested heavily in technology; these investments have come from all levels of the system—federal, state, and local. In 2019 alone, the Federal Communication Commission granted 1.9 billion dollars of federal funds to expand high speed internet access to schools (Federal Communication Commission, 2020). In seven years, K-12 school laptop and tablet purchases increased by 363 percent, from roughly 3 million devices in 2010 to almost 14 million in 2017 (Bushweller, 2017). New York State, in which the region being studied is located, voted to allocate an additional $2 billion to technology and infrastructure through the Smart School Bond Act to "improve learning and opportunity" (Smart Schools Bond Act, 2014). While technology investments have been motivated by their perceived utility in personalized learning, there is little consensus on how to effectively use technology to personalize learning. Preliminary evidence shows that technology can either be an expensive detractor from or a promising tool for personalized learning. Further study of technology for personalized learning needs to be conducted to shed light on how to best use scarce human and technological resources.

Purpose of Study

The purpose of this quantitative study is to explore patterns in teacher reported implementation of personalized learning between and within participating Long Island schools and districts. Technology leaders in Long Island are provided drastically different district budgets from which to allocate spending in coordination with state and federal bonds, grants, and earmarked aid. Long Island is an economically and racially diverse, yet segregated region. While 92% of high poverty schools' student body is either Black or Hispanic, low poverty Long Island school student bodies are 93% White or Asian

(Golob & Douzinas, 2018). These disparities raise concerns for educational equity. The difference in expenditure between the top and bottom 10% of school districts in Long Island was reportedly upwards of $6000 per student in 2015 (Mangino & Silver, 2015). The five districts included in this study varied in per student expenditure upwards of $8,000 last year (Ebert & Hildebrand, 2020). E-rate and New York State's Smart Schools Bond Act provide funds to districts in proportion to need but fall short of providing the human infrastructure and software systems required to adequately support instructional technology towards personalized learning. Earmarked federal and state funds intended to aid the poorest districts restrict purchases to hardware related to district connectivity, network hardware, or devices. This study will assess how unfunded variables like home internet access, software, and human resources relate to espoused personalized learning goals, in comparison to and coordination with funded investments in hardware, school internet access, and devices.

Sections of a published teacher survey designed by RAND (Pane et al., 2017) will serve as a tool to assess teacher-reported personalized learning. The same survey questions were used in the published RAND study to correlate personalized learning with higher student achievement. Variation in personalized learning will be analyzed in relation to student device access, student access to high-speed internet, student use of a centralized learning management system, and dedicated human resources to support technology.

Theoretical Foundation and Conceptual Framework

As change theory warns and COVID-inspired shifts to remote learning have proven, personalized learning does not occur simply because new classroom and student technology is introduced. According to Fullan (2004), authentic instructional change occurs as a result of moral purpose, collaboration, and coherence making. Change theory warns us against using technology instead of pedagogy as a motivator for change and describes how to maximize professional capital towards the student-centered practices at the heart of personalized learning (Hargreaves & Fullan, 2012). Technology only supports continuous and authentic instructional improvement when it is used by the teacher to leverage or enhance pedagogy. Change does not occur by means of a technical "fix," device or curricula, but in the relationships between "professional and community interests that are worked out in the day-to-day activities in the schools" (Popkewitz et al., 1982, p. 179). Acknowledging the potential and limitations of technology in education, Fullan and Smith (1999) envisioned that technology could be leveraged to meaningfully change student learning if leaders remained focused on "the teacher as learner, organizational learning, and program coherence" (Fullan & Smith, 1999, p. 7). How teachers are invited to use technology to change pedagogy is at the root of educational change.

According to change theory, our ability to successfully leverage technology in pedagogy relies on our investment in professional capital. Teachers, not technology, will change education from being schools from being "places" of "knowledge instruction" to opportunities for students to engage in "knowledge construction" (Fullan & Smith, 1999). Personalized learning, like change theory, defines the attributes of "student knowledge construction" as the desired state of continuous institutional learning. This study seeks to operationalize variables that contribute to schools' capacity to support personalized learning and thereby support meaningful instructional change.

In this study, technology and its diverse components are conceptualized as a potential catalyst for achieving personalized learning with greater ease. As discussed above, personalized learning can occur without technology; however, technology may enable broader and deeper use of personalized learning strategies in the classroom. Variations in student device and internet access, consolidated use of software, and dedicated human resources, were explored in relation to teachers' use of personalized learning strategies in the classroom. While I hypothesized that no one technological variable would, in isolation, covary with personalized learning strategies, I expected significant differences between districts in personalized learning because of interrelated technological support variables and/or district-specific initiatives.

Rationale and Significance

Exploring variation in personalized learning could reveal where and how to invest resources to achieve meaningful technological change. Prior federal and state investments in technology, like the Smart Schools Bond Act and federally allocated e-Rate funds, supported connectivity projects to provide high-speed internet and device access to all students. Excluded from use of these funds are the software and human resources found throughout literature to account for differences in the quality of school and district implementation of personalized learning. Studying if and how these variables significantly contribute to personalized learning could inform school and district spending on technology.

Moreover, this study provides timely insight into the landscape of personalized learning on Long Island and the contribution of factors towards which leaders are currently allocating resources throughout the COVID-19 global pandemic. Teachers and students rapidly shifted daily instruction online, forcing world-wide recognition that learning takes place within students, not classrooms. One of the biggest challenges to our schools, in this transition to fully online education, is getting students to "show up" online and intellectually engage once they do. An understanding of personalized learning offers guidance to students, parents, teachers, and educational leaders who are struggling to budget and plan for personalized digital learning during and beyond the COVID crisis.

Connection with the Vincentian Mission

This study directly aligns with the university's commitment to reflective learning and social justice inspired by St. Vincent de Paul. Conceptual models set forth in this study are intended to reveal systemic inequities in funding for educational technology that disadvantage students in Long Island's poorest communities. In pursuit of the same empowerment for positive change stated in St. John's Vincentian Mission, this study aims to identify and remove obstacles to achieving personalized learning for students throughout the region.

Research Questions

Research Question 1. Does personalized learning (PL) vary within and between school districts on Long Island?

Research Question 2. How do districts' average student device access relate to teachers' use of personalized learning?

Research Question 3. How do districts' average student home and school internet access relate to teachers' use of personalized learning?

Research Question 4. How do districts' LMS usage relate to teachers' use of personalized learning in a district?

Research Question 5. How does the total number of dedicated technology faculty (FTE) in a district relate to teachers' use of personalized learning?

An electronic survey was used to measure teacher reported indicators of personalized learning. A mixed model analysis was used to determine how personalized learning and its subcomponents varied within and between districts. Regressions were used to estimate the predictive power of technology support variables on personalized learning and its five subcomponents.

Definition of Terms

Personalized Learning: "a progressively student-driven model in which students deeply engage in meaningful, authentic, and rigorous challenges to demonstrate desired outcomes" (Kallick & Zmuda, 2017).

1:1 Device: each student has a dedicated computing device to use as a learning tool, often in the form of a laptop or tablet

High-Speed Internet Access: reliable access to and use of online classroom content and virtual meeting spaces

Learning Management System: a software that integrates instructional tools, parent, student and teacher communication, and data from student management systems.

Full Time Employee (FTE): part or whole of an appointed school or district position

CHAPTER 2

This chapter contextualizes literature on personalized learning and its relationship with technology and change in education. Conceptual models are proposed to relate variables found in literature on educational technology as critical to the study of personalized learning. A review of literature on 1:1 student device access, student internet access, learning management systems, and technology dedicated human resources were connected to the operationalization of personalized learning.

The History of Technological Change in Education

Despite vast promises and hope, technology has historically failed to change instruction and improve student achievement. In *Teachers and Machines*, Larry Cuban (1986) provided a historical account of the introduction of film, radio, television, and early computers into U.S. education. Cuban evidenced the repeated cycle of external excitement for the potential of each technology to "revolutionize" education and the stagnancy of classroom practices in the face of implementing that technology. For example, Cuban documents that the introduction of film to education began with Thomas Edison's claim that the motion picture would revolution our educational system (Cuban, 1986). A few decades later, grants from the Ford Foundation's Fund for the Advancement of Education and funds from National Defense in Education Act of 1958 invested millions of dollars into classroom television (Cuban, 1986). Throughout the next decades, publications documented the positive impact of television in the classroom as a total instructional program, a supplemental tool, or a teaching aid. However, by the early 1980s, analysis of seven relevant articles evidenced that on average, teachers used television during class only as an accessory to learning for between 30 and 60 minutes per week (Cuban, 1986). Film, radio, and television, and early computer implementation in classrooms followed the same pattern. First, money, research, and attention were focused on the latest technology. Then, the technologies were minimally adopted in as much as they fit into the existing structure of teachers' classrooms.

In 1983, the push to introduce technology into classrooms was renewed with the National Commission on Excellence in Education's publication of *A Nation at Risk* (Tyack & Cuban, 1995). The report detailed the failures of our nation's schools and contrasted the changing global needs emerging from technological innovations with the tendency of our national system of education to remain "idle" (*United States Department of Education,* 1983). Since this report, Tyack and Cuban argue that our schools looked towards computer-based technologies with "hope for easy solutions to educational problems and profits from pedagogy ... New reformers, salespeople, and political allies would come again to promise that the private sector could succeed where the public 'establishment' had allegedly failed" (Tyack & Cuban, 1995, p. 120). Schools purchased computers throughout the 1980's and 90's, but quickly realized that similar to prior technological initiatives, "Simply having access to computers and learning to use them as tools is only part of the story of the educational use of computers" (Tyack & Cuban, 1995, p 125).

While early computers, like their technological predecessors, were not incorporated into regular instructional practices, Ferster (2014) communicated a cautious optimism about computer-based educational technology. Computer technology advances, Ferster noted, outpaced improvements seen in any mechanical technologies that proceeded it. Ferster researched the potential of user centered design and intelligent tutoring systems that provide granular skill-based feedback in education. While responsive computer-based learning offered productive opportunities for development, Ferster noted that these machines could not compare to the limitless potential of human expertise.

Today, the potential and limitation of computer-based technologies has become an increasingly important conversation. As a result of the COVID-19 pandemic in 2020, students were physically separated from teachers, and education became 100% reliant on computer technology. Students and teaches used it for all communication: instruction, homework, and feedback. Those without computing devices and/or internet access could not access these tools at all. Those with devices and internet access at home could engage in virtual classes, use responsive programs, and receive feedback. However, while device and internet access are prerequisites for student access to digital learning experiences, teacher practice and pedagogy emerged as the most important factor in students' experience during COVID-19 stay at home orders (Cuervas, 2020). In other words, although technology has improved and become indispensable within education, teachers still drive how that technology is used and what technology-assisted instruction looks like.

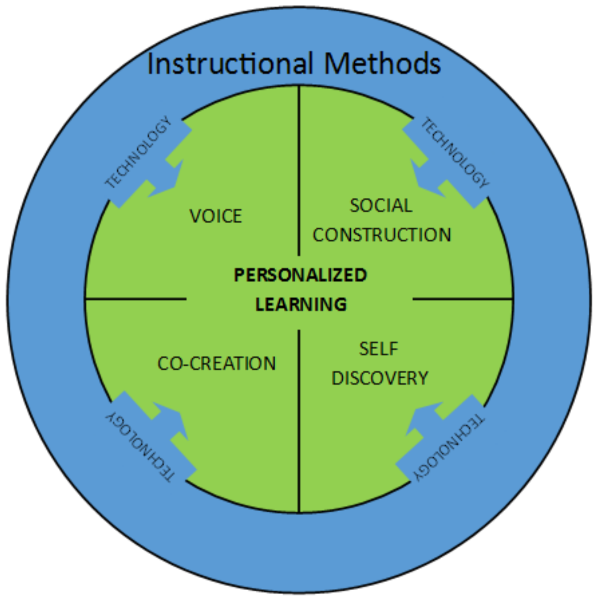
Conceptual Framework

This study is designed to assess the landscape of personalized learning in Long Island and to explore variance related to technological access and resources. Kallick and Zmuda distinguish strategies like individualization, differentiation, and digital learning as tools utilized to implement personalized learning (Kallick & Zmuda, 2017). The authors clarify that "individualization… allows for instructional learning to happen anytime and anyplace… Students are assigned the learning tasks, and they go on to [often] use technology… to [independently] complete those tasks" (Kallick & Zmuda, 2017, p. 5). Individualized instruction is a part of personalized learning. But personalized learning, in contrast with individualized learning, also incorporates the relational part of learning, involving students in the design and development of engaging and relevant learning tasks. These relational aspects of personalized learning are what many during the COVID-related school closures are pointing to as "missing" in many versions of digital learning (Klein, 2020). Numerous educational technology companies like DreamBox Learning, Pearson, EdGenuity, and Prodigy offer responsive products that differentiate content and feedback using conditional pathways or competency-based progressions. Prescribed responsive course progressions individualize and differentiate learning, but they are not necessarily indicative of personalization as defined in this study.

As the title of Kallick and Zmuda's book clarifies, personalized learning engages and empowers students to be a part of designing their learning (Kallick & Zmuda, 2017). Kallick and Zmuda provide four attributes of personalized learning through which classroom practices and goals could be examined (illustrated in green in Figure 1): 1) student voice in what is learned and how it is learned; 2) student co-creation of learning goals and assessments; 3) students' social construction of ideas with others in a learning community; and, 4) student self-discovery or reflection on learning and how it applies to life (Kallick & Zmuda, 2017, p. 3). These attributes are therefore at the center of this study's conceptual framework, the goal of personalized learning. A teacher survey designed by the RAND Corporation (Pane et al., 2017) were used in this study as a proxy for assessing the degree to which the attributes of "personalized learning" are being implemented, as per the conceptual framework above.

Figure 1

A Conceptual Framework for Personalized Learning

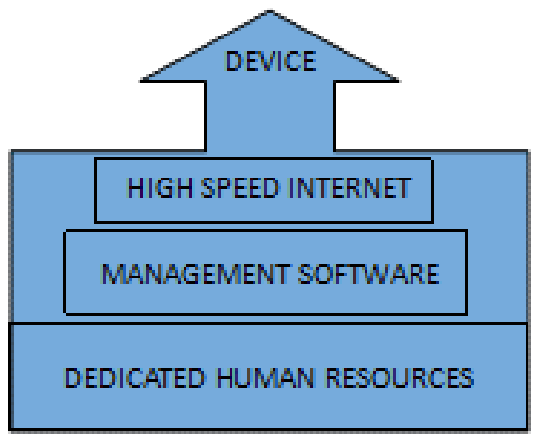


The blue area in Figure 1 symbolizes the diverse instructional methods that contribute to personalized learning environments. Bray and McClaskey call instructional methodologies used in personalized learning the Class Learning Toolkit (CLT). The CLT includes strategies and tools for students to "access, engage, and express" learning (Bray & McClaskey, 2017, p. 91).

This study is intentionally focused on the mitigating effect of technology-embedded variables and how they can act as conduits between instructional methods and personalized learning (as shown in the arrows in Figure 1). Based on the literature review below, this study categorizes mitigating technology-embedded variables into four parts: 1) device access, 2) high speed wireless internet access, 3) software, and 4) dedicated human resources (Figure 2). As illustrated in the model below, a student device serves as the medium through which a student uses computer technology towards achieving personalized learning. The relationship between student device access and personalized learning may vary greatly, depending on internet and software access, as well as dedicated technical and instructional human resources supporting its productive use.

Figure 2

Hierarchical Model of Technology Embedded Variables



Variation in the proportion of students with a) in-school and b) home 1:1 computer device access and high-speed internet access were assessed via a teacher survey. Teacher, student, and parent use of a) a learning management system (LMS) and b) learning management systems (LMS) with student management system (SMS) pass-back and parent communication, were used as an indicator of software management within the district. Finally, dedicated instructional and technical full-time faculty and staff counts will be calculated per student as the measure of dedicated human resources. Survey responses within district will be cross-referenced between respondents and school and district technology leaders. Findings from this study revealed to what degree personalized learning varies with technological support within and between Long Island districts.

Personalized Learning

The National Educational Technology Plan (NETP) defines personalized learning as “instruction in which the pace of learning and the instructional approach are optimized for the needs of each learner... Learning activities are meaningful and relevant to learners, driven by their interests, and often self-initiated" (United States Department of Education, 2017). Schmid and Petko (2019) share a review of commonalities in literature about personalized learning, referencing the NETP and its increased focus and use of the term. They state that personalized learning can be understood as an “umbrella term for tailor-made educational approaches ...that subsumes adaptive and individualized teacher-led instructional methods in combination with self-directed student activities in open learning environments in which students’ choice and voice is encouraged” (Schmid & Petko, 2019, p. 77). Schmid and Petko’s review of literature evidence a convergence of academic personalized learning attributes aligned with those put forth by Kallick and Zmuda (2017): student voice, co-creation, social construction, and self-discovery. This study explores how schools operationalize personalized learning, the evidence of the inextricable relationship between technology and the systematization of personalized learning, and the published outcomes of implementation.

Operationalizing Personalized Learning

A large-scale study of 308 “learner-centered” schools categorized the implementation of personalized learning to include at least three of the following: 1) the use of personalized student learning plans; 2) competency-based student promotion; 3) criterion-referenced assessment; 4) problem or project-based learning; and/or, 5) multi-year mentoring (Lee et al., 2018a). While terminology describing the operationalization of personalized learning differs slightly among published literature in the field, there is convergence around these five characteristics of personalized learning environments. For example, the use of personalized student learning plans is expressed in some articles as data-based paths (Steiner et al., 2015; Pane et al., 2017; Schmid and Petko 2019) summarize the operationalization of personalized learning to “adaptive and individualized teacher-led instructional methods in combination with self-directed student activities in open learning environments in which students’ choice and voice is encouraged” (Schmid and Petko, 2019, p. 77). Common to all definitions is that personalized learning practices are intended to adapt to student needs and develop learner agency (Bray & McClaskey, 2017). Also common to all literature on personalized learning, is recognition that technology is essential to managing the complexity of personalized learning in a classroom environment (Huggins & Kellogg, 2020). Technology-based learning management systems, responsive competency-based programs, and student devices and software provide an ease of access, engagement, and expression to personalize learning in ways previously impossible (Lee et al., 2018b).

Role of Technology in Personalized Learning

Technology provides learners ease of access to resources and diverse methods of engagement and expression otherwise impossible. A meta-analysis of 18 quantitative studies found a relationship between technology and learner-centered instruction (Karich et al., 2014). Variables like pacing, time-allocation for mastery, sequencing of instructional materials, choice in practice item, and amount of review materials led to the highest effect sizes on achievement outcomes when controlled by learners (not by the teacher or program). In these studies, learner control within educational technology led to a larger effect on behavioral outcomes ($g = 0.19$, 95% CI = -0.12 to 0.50) than academic outcomes ($g = 0.00$, 95% CI = -0.14 to 0.14) (Karich et al., 2014). Although effect sizes were small and there were some overlapping indicators, the relatively higher effect for behavioral variables may point to learner control improving motivation, engagement, and self-efficacy.

While technology is widely recognized as a beneficial tool for teacher guided personalized learning, there is growing concern that there is a misguided technological focus of modern personalized learning. Critics warn that too great a dependence on technological tools may actually undermine student voice, choice, co-creation and self-discovery and the value of skilled teachers to the benefit of large technology companies (Kim, 2019; Walkington & Bernacki, 2020).

This study was also designed around concerns for equity among schools and districts deficient in reliable resources or funding. A collective case study of 28 schools implementing a common vision for personalized learning concluded that issues and gaps in the reliability of technological resources detracted from the learner centered goals of personalized learning (Bingham et al., 2018). Three years of interviews, focus groups, observations, and survey data from 2012-2014 found that 25% of participating teachers experienced hardware problems and 35% experienced internet or bandwidth issues while using technology to personalize learning. Technological devices were also being abused in ways that did not support student learning. Authors concluded that technological tools, infrastructure, and professional development were insufficient to support teachers' personalized learning goals (Bingham, et al., 2018). Implementing personalized learning in classroom environments was found to be conditional on the presence of both reliable technology and a student-centered learning environment.

Personalized Learning Outcomes

Xie et al. (2019) conducted a literature review of educational technology articles about personalized learning published between 2007 and 2017. Researchers searched the Social Sciences Citation Index (SSCI) and its 3200 journals for articles that included "personalized learning" or "adaptive learning" in the field of education/educational technology research and found 144 publications (Xie et al., 2019). By filtering out those that did not focus on adaptive, personalized e-learning systems or activities for personalized teaching and learning, the authors identified 70 articles that met the criteria for inclusion in the study. Researchers found that 38 of the 70 publications conducted studies in the K-12 setting, with the remainder conducted in higher education settings. Despite the focus of personalized learning on competency-based progressions, engagement, and self-efficacy, most publications were found to focus on student or teacher affections and cognition instead of skills and behaviors (Xie et.al, 2019). Similarly, there was a greater focus of research on achievement rather than higher order thinking or collaboration and communication. K-12 indicators of personalized learning, like improved engagement, self-efficacy, skill improvement, habits of mind, collaboration or communication were included. Authors concluded that measuring the efficacy of adaptive technologies is limited by the dominant use of conventional indicators of achievement unrelated to many of the goals of personalized learning.

In Basham's 2016 study of student achievement in 12 large urban schools implementing personalized learning (Basham et al., 2016), data indicates significant benefits of personalized learning to students' learning growth. Researchers noted that the statistical likelihood of meeting at least 1-year academic growth in both Math and English Language Arts increased by 5% (OR = 1.05) with each 100 or more days enrollment in the school (Basham et. al., 2016). These gains were irrespective of special education status, highlighting the universal positive impact of personalized learning on student achievement regardless of learning need (Basham et. al., 2016).

One of the most rigorous, large-scale, and widely referenced publications on the effect of personalized learning on improved student achievement was conducted and published by the RAND Corporation (Herold, 2016). *Continued Progress: Promising Evidence on Personalized Learning* (Steiner et. al, 2015), a study of 62 public charter and district schools and the achievement of their 11,000 students, showed that compared to peers, students in schools using personalized learning practices in grades K-8 made greater progress over the course of two school years in both math ($r = 0.27$, $p <. 05$) and reading ($r = .19$, $p < .05$). Over a three-year period, this treatment effect was found to increase.

The follow-up study, *Informing Progress: Insights on Personalized Learning Implementation and Effects* (Pane et. al, 2017) was intended to revisit personalized learning with the lens of how educational technologies are further supporting student success. Teacher (241 participants) and student (6435 participants) Likert surveys were used to measure the degree of personalization of instruction and relate it to both the reported quality of available technologies and change in student achievement on the

NWEA MAP exam relative to comparable students' progress. Positive, albeit small, treatment effects, of approximately 0.09 in mathematics and 0.07 were found, which translate into gains of about 3 percentile points, from higher levels of personalized learning ($p < .05$) (Pane et. al, 2017). Research indicates some significant positive effects of personalized learning in large-scale research. In close analysis of which schools struggled and which thrived, data evidenced higher yet statistically insignificant gains among schools implementing a higher degree of personalized learning.

Personalized learning has been found to both have a measurable positive impact on student achievement and be best supported through technology. The intention of this dissertation is to determine which elements of technology most significantly impact personalized learning. Using the same established teacher survey tools developed by the RAND Foundation (Pane et.al., 2017), this study determined the relative contribution of student access and use of computer devices, internet, learning management software, and human resources dedicated to support technology.

Student Devices

A meta-analysis of 96 experimental and quasi-experimental publications on student 1:1 laptop device access from January 2001 to May 2015 (Zheng et al., 2016) found positive significant differences in Math and English Language Arts (ELA) achievement between groups of students with and without 1:1 devices. Yet only the ELA subcomponent of writing ($I^2 = 64.89\%$, $Q = 29.03$ ($p < .01$), $d = .20$) was found to have a significant effect size when comparing groups of students with and without 1:1 devices. Writing assignments were also found in nine studies to be more diversified and authentic when students had 1:1 laptop access, which Zheng et al. attributed to ease of use and editing of writing. In the article, Zheng et.al. shared data showing that access to 1:1 devices increases the use of technology for learning (4 studies), increases student-centered (11 studies) and individualized (11 studies) instruction, and improves teacher-student communication, home-school continuity or relationships (12 studies) (Zheng et.al., 2016). These studies also suggest the greater impact of 1:1 device programs on students of low socioeconomic status; increasing ease of use and familiarity with technology and yielding more academic gains (Zheng et.al., 2016). The meta-analysis, overall, indicates a positive yet varied impact of 1:1 student device access on productivity, home-school communication, use of technology, student-centered instruction, and achievement, with the greatest impact on the lowest achieving population.

One study, included in the previously described meta-analysis, stood out because of its distinction between 1:1 based improvements in productivity versus instruction/instructional delivery. The three-year (2005-2008) mixed-methods study of the Berkshire Wireless Learning Initiative (BWLI) found a significant but small predictive factor of BWLI participation on the ELA component of Massachusetts Comprehensive Assessment System (MCAS) performance ($p <.05$), but not in Math (Bebell & Kay, 2010). Bebell and Kay (2010) found the number of words used in written portion of the MCAS was greater for those testing on their 1:1 laptop than using traditional paper and pencil ($F=19.95$, $p < .001$, adjusted $r^2 = .256$). Specifically, students who completed the writing assessment using their laptop produced an average of 388 words compared to 302 words for the essays composed on paper across all BWLI settings. Bebell and Kay (2010) found no impact of 1:1 laptop access on measures of observed collaboration among students and no indicators, outside of teachers' self-reported changes and positive perceptions of impact, of significant changes in observed or reported teaching strategies and curriculum delivery.

A more recent study of 18 diverse elementary, middle and high school classrooms provided further insight into the relationship between student 1:1 device access and personalized learning (Varier et al., 2017). Teachers reported increases in student independence, more initiatives for self-directed learning, and student learning extending beyond the classroom. Teachers attributed greater student independence to the ease of providing "immediate" and "formative" feedback using devices. Student interviewees provided similar feedback. A middle school student explained that students were able to read each other's work and discuss it. Middle and high school students also communicated their belief that device access lessened gaps in achievement "because all students can search for answers independently" (Varier et al., 2017, p. 982-983). Increased communication, engagement in formative self and peer assessment and greater independence in learning are all tools that support increased personalization.

A three-year longitudinal mixed-method study of iPad use in a middle school illustrated similarly positive teacher-reported perceptions, in addition to significant academic gains made by the lowest and highest achieving populations, and trends in increased home-use of devices (Tay, 2016). Of the 13 teacher respondents, 3 (23%) felt that the iPad was useful as a teaching and learning tool while 8 (61.5%) rated it very useful and 2 (15.4%) rated it extremely useful. Participation in the iPad initiative was significantly, positively correlated with academic achievement in the first and second year of participation ($F = 5.33$, $p < .05$ (2011), $F = 5.172$, $p < .05$ (2012)). When correcting for incoming ability, data indicated that participation in the 1:1 iPad program was a significant factor among students in the lowest achieving quartile of the incoming cohort ($t = -3.28$, $df = 132$, $p < .05$ (2011) and $t = -3.17$, $df = 132$, $p < .05$ (2012)) and highest achieving quartile ($t = -3.92$, $df = 59.90$, $p < .05$ (2011) and $t = -3.39$, $df = 48.06$, $p < .05$ (2012)). Access to 1:1 iPad devices most significantly impacted the achievement of the lowest and highest achieving student participants (Hui, Y.T., 2016). These trends contextualize the potential impact of 1:1 student device access to enable higher degrees of personalized learning.

Research shows that 1:1 student device access most positively and significantly impacts our highest and lowest achieving students, increases student productivity, and increases student independence. This dissertation adds to this body of literature by exploring how 1:1 device access varies with personalized learning, in addition to how home and school high-speed internet access, use of a learning management system and dedicated technology human resources covary.

Student Internet Access

High-speed internet access at home and school contribute to the utility of technology for personalized learning. A meta-analysis of 30 theoretical articles and 49 empirical studies published between 2005 and 2015 contextualizes the changing definition of and widening gap in students' digital access at home and at school (Dolan, 2016). Digital access is defined as that which enables students to actively use technology instead of passively consume it. Studies found that those who are of low socioeconomic status are less likely to have access to a computer connected to the internet than those of high economic status (Dolan, 2016). The American College Testing (ACT) organization conducted a study of student home and school internet that evidences similar gaps in computer-based internet access between those of low and high socioeconomic status (Moore & Vitale, 2018). Of the 7233 students surveyed, 99% have access to the internet at home. Of those students, 75% use a monthly cellular data plan and only 36% have access to broadband. Of the students with the lowest reported annual family income range, 23% had one device, usually a cellphone, whereas 9 and 5% of students in highest two income brackets only had one device. A focus on 1:1 device programs, in the absence of high-speed home internet access, may exacerbate inequities in digital access to instructional opportunities and resources.

Another study revealed significant differences in academic behaviors and performance based on student high speed computer access (Hampton et al., 2018). Data from a survey of 3258 eight to eleventh grade students from 173 classrooms in Michigan were analyzed using hierarchical linear modelling to determine the relationship between student home internet access and various other variables like income, ethnic, and racial status, as well as parental marital status and education (Hampton et.al., 2018). Speed of home internet access tests were conducted to cross-reference students' self-reported measure of internet speed as slow or fast with significant differences verified between groups ($p < 0.01$). When controlling for all other demographic variables (income, minority status, parental education, and digital skill level) the largest degree of variance in homework completion rates correlated most with student internet access ($p < .01$). Yet, those who have no internet access at all spend 30 minutes more on average on homework than their peers who have high-speed internet ($p < 0.01$) (Hampton et.al., 2018). This report evidenced that high speed internet access at home may have a significant impact on personalized learning, in terms of students' out of school experiences.

Personalized learning, as defined in this study, relies on a student having agency and voice in his or her learning. There were significant differences in self-reported engagement in online activities outside of school ($p < 0.001$) between groups of students based on home internet access. Students without reliable high-speed home internet access were significantly less likely to research, create online documents, work with peers on projects, message a classmate for help, text or message teachers with questions or video chat with classmates about schoolwork than their peers with reliable internet access. Differences in students' agency to continue learning and work outside the classroom may significantly limit the intended benefit of 1:1 device initiatives, and consequently limit personalized learning (Hampton et.al., 2018).

Differences in school internet access were found to potentially exacerbate inequities in home access. More students rated their school internet access as "terrible" or "unpredictable," than their home internet. Researchers concluded that "the gap between people who have sufficient knowledge of and access to technology and those who do not can perpetuate and even worsen socioeconomic and other disparities for already underserved groups" (Moore & Vitale, 2018). 1:1 device initiatives and inequities in home and school internet access may widen differences in student access to technology-based learning experiences.

In 2019 alone, the Federal Communications Commission (FCC) allocated over 4.5 billion dollars to support internet access for schools and libraries within the e-Rate program set forth in the Telecommunications Act (1996). Based on enrollment and need, schools apply for allocated federal funds for internet services or the hardware required to provide high speed internet access in schools. Despite these ongoing investments, our rapid transition to digital learning, as a result of COVID-related stay-at-home orders, evidenced the persistent inequities in home computer device and internet access. As a result of a petition written by 7662 educators in May of 2020, the FCC is now considering including home internet access as an approved use of FCC funds (Schaffhauser, 2020). This study informs investments in home and school internet access by assessing to what degree home and school high speed internet access contribute to variations in personalized learning; how students are using the internet at home.

Learning Management Systems

Personalized learning, as defined above by academia, public, for-profit, and non-for-profit companies relies on efficient teacher, student and parent access to learning resources, tools, and data. A comprehensive learning management system (LMS) is a software that integrates instructional tools, parent, student and teacher communication, and data from student management systems. In this study, LMS adoption serves as a proxy for school and/or district commitment to or investment in systems through which to clearly communicate about and monitor student progress.

Most post-secondary institutions in the United States have used LMS's to support administration, instruction, and online courses for over 15 years. In 2005, it was found that 90% of the higher academic institutions in the United States provide its courses and programs via LMS platform (Jones et al., 2005, p. 219). Secondary schools are increasingly adopting LMS platforms based on these benefits. A sample of 105 secondary school teachers of the 2500 in a large district in Texas were surveyed regarding the use of a learning management system the district adopted. When surveyed, the perceived usefulness of a learning management system was found to be the most important factor in planning to adopt it (Stockless, 2018) (Wraikat et al., 2017). Pairwise comparisons of median Likert-survey data from another study showed that those with 25 years of teaching experience or more shared educational resources through the LMS (M=5.00 (Never)) less frequently than teachers with 6–10 years (M = 3.00 (bi-weekly), p = .009), 11–15 years (M = 2.00 (weekly), p = .003), and 16–20 years (M = 4.00 (monthly), p = .009) (Laho, 2019). Interestingly, Kruskal-Wallis H testing showed that greatest statistically significant differences in use were found to depend on differences in years of experience in using the LMS (H = 12.707, p = .026). In other words, familiarity with the LMS increased teacher usage of the software. In fact, a study of 2573 instructors and 4537 students revealed overall more positive results in all surveyed about the LMS in the second year of implementation (Lonn & Teasley, 2009). The longer teachers practice using an LMS the more likely they are to use it to share educational resources with students.

Modern LMSs are evolving from platforms for instructional access and delivery to responsive systems that support adaptive personalization (Dagger et al., 2007). Use of leaning management systems by both teachers and students was found in common among 12 large urban schools with an explicit vision of implementing personalized learning (Basham et.al., 2016). LMSs like Canvas, Blackboard, SeeSaw, Schoolology, and Google Classroom have the capacity to also integrate with student information systems to provide ongoing performance data. In addition to providing a “one-stop” virtual classroom environment from which to access instructional software, these LMSs offer tailored student, teacher, and parent-facing products. Of the teachers surveyed in another study of secondary school adoption of an LMS, 44.6% reported using the LMS to post student announcements, 36.9% to assign homework, 36.9% to provide information to parents and 15.3% to conduct two-way communication with parents (Laho, 2019).

Students' and parents' ability to monitor progress along personal learning paths relies on meaningful access to student information and tools for parent communication. Grade pass-back or a parent-facing communication through an LMS is used to distinguish two levels of LMS adoption among teacher participants in this study.

Dedicated Human Resources for Technology

Skilled leaders, technicians, and instructional technology coaches determine the success of implementing personalized learning. Few articles discuss human resource allocations to support personalized learning. What has been shown is that reliable technological infrastructure and collaborative professional learning are integral to the successful implementation of educational technologies. A three-year mixed-methods study examined student and teacher expectations, concerns and perceptions of implementing a 1:1 program in an Australian Catholic, coeducational secondary school (Keane & Keane, 2017). Researchers assessed the success of programs by examining student and teacher use and reported satisfaction. Of the five student groups participating in this study, the results deemed one unsuccessful group, another less successful than expected and three successful programs. The authors concluded that one of the four main factors of success was a stable technological infrastructure (Keane & Keane, 2017). Assembling idiosyncratic technology ecosystems to distribute teaching and learning tasks was identified as one of three leadership macro tasks critical to school implementation of personalized learning (Kallio & Halverson, 2020). Skilled technical support is a prerequisite for setting up and supporting these idiosyncratic systems to personalize student learning.

Studies have found that technology support also influences teachers perceptions of initiatives as well as their success in achieving the goals of the respective initiatives (Ifenthaler & Schweinbenz, 2016). Technical, curricular, and pedagogical support for technologies are important components of programmatic success (Zheng et al., 2016). The increasingly complex technical landscape of personalized learning poses technical challenges that require more collective technical knowledge and skill. Protecting student data, merging diverse software platforms, developing sufficient network and wireless infrastructure, and maintaining devices are critical, new, minimally researched components of supporting personalized learning. The degree to which dedicated technology human resources per student impacts personalized learning is examined in this dissertation. Human capital dedicated to the support of personalized learning technologies has never been as difficult or important to student learning.

Conclusion

This study explores the role of technology as an instructional catalyst through which teachers personalize learning. Technological factors such as device and internet access, use of an LMS, and dedicated human resources are analyzed in relation to personalized learning and its subcomponents. Findings could inform criteria for federal, state, district and school investments in technological hardware, software, and human resources.

CHAPTER 3

The purpose of this study is to understand the variation in teachers' reported use of personalized learning and how it relates to teachers' access to technological devices and infrastructure. An electronic survey based on a 2017 RAND Corporation study (Pane et al, 2017) was used to measure teacher reported indicators of personalized learning. Teacher survey items related to technology support, including 1:1 student device access, home and school internet access, LMS usage and per student dedicated technology staff were aggregated to the district-level and used to predict their use of personalized learning.

Research Questions and Null Hypotheses

Research Question 1. Does personalized learning (PL) vary within and between school districts on Long Island?

H_0: There is no statistically significant variation in personalized learning within or between the Long Island school districts studied, $\tau^2 = 0$.

Research Question 2. How does districts' average student device access relate to teachers' reported personalized learning?

H_0: The percent of teachers reporting access to devices in school only or at home and in school will explain no between-district variance in personalized learning, $R^2 = 0$ for all outcomes: personalized learning (PL) and its subcomponents; personalized learning plan (PLP), student centered (SC), student voice (SV), competency-based assessment (CB), and project-based learning (PBL) composite personalized learning score.

Research Question 3. How does districts' average student home and school internet access relate to teachers' reported personalized learning?

H_0: The percent of teachers reporting reliable school internet access will explain no between-district variance in personalized learning, $R^2 = 0$ for all outcomes: PL, and PLP, SC, SV, CB, and PBL composite personalized learning score.

H_0: The percent of teachers reporting most or all students having internet access at home will explain no between-district variance in personalized learning, $R^2 = 0$ for all outcomes: PL, and PLP, SC, SV, CB, and PBL composite personalized learning score.

Research Question 4. How do districts' LMS usage relate to teachers' reported personalized learning?

H_0: The percent of teachers reporting using LMS for assessment and parent communication will explain no between-district variance in personalized learning, $R^2 = 0$ for all outcomes: PL, and PLP, SC, SV, CB, and PBL composite personalized learning score.

Research Question 5. How does the total number of dedicated technology faculty in a district relate to teachers' reported personalized learning?

H_0: The total FTEs per 1000 students will explain no between-district variance in personalized learning, $R^2 = 0$ for all outcomes: PL, and PLP, SC, SV, CB, and PBL composite personalized learning score.

Instruments

Access to Technology Resources

The teacher survey used in this study (Appendix A) included items designed by the researcher to acquire information related to teacher and student access to technology resources. Survey items were sent to teachers and administrators from a district that did not participate in this study for review. Feedback was used to edit and improve item wording for clarity. Teacher responses were averaged by district to provide mean data on devices, internet access, LMS usage. Full-time employee data was provided by technology directors at respective schools and districts. A phone interview was used to clarify and/or contextualize leader reported data.

Personalized Learning

Items of a teacher survey (Appendix 3) published by the RAND Corporation (Pane et.al., 2017) were adapted and used with permission (Appendix 4) in this quantitative study. This tool was selected because the questions aligned with referenced definitions of personalized learning. Questions used succinctly captured the personalized instructional practices in a Likert survey, with responses ranging from 1 (not at all/strongly disagree) to 4 (a great extent/strongly agree). Although not perfectly aligned with Kallick and Zmuda's attributes, the items of this personalized learning teacher survey overlap the attributes illustrated in green that describe personalized learning environments. The 23 personalized learning teacher survey questions used in this study measure: 1) characteristics of student learner profiles (8 items); 2) student choice and engagement (5 items); 3) project-based learning (3 items); 4) student awareness of goals and progress (3 items); and5) competency-based learning implemented in classrooms (4 items). These survey components closely mirror the attributes of voice, co-creation, social construction, and self-discovery found in the green "core" of personalized learning illustrated above. Survey items were included in this study in the same order in which they appear in the original survey (Pane et. al, 2015).

The Cronbach's alpha reliability statistics from the original survey study were acceptable (Fraenkel, Wallen, & Hyun, 2012 p 157) for characteristics of student learner profiles (α =0.91) student choice and engagement (α =0.77) project-based learning (α =0.86) student awareness of goals and progress (α =0.71) and competency-based learning implemented in classrooms (α =0.81). Participant responses for overall measures of personalized learning and the respective components in this study will be coded and averaged in the same manner as the RAND survey. RAND survey items related directly to technology were omitted from this study to avoid conflating personalized learning and technology variables being studied.

Population and Sample

This study was conducted in five Long Island public school districts, including K-12 teacher participants from 27 schools. Through assistant superintendents and technology directors with whom the researcher has regular contact, respective superintendents provided permission to conduct this study.

Data Collection Procedures

Unique school-specific copies of each survey were made in Survey Monkey for each participating school. Administrative contacts within each district internally distributed the teacher survey to teachers via emailed Survey Monkey link. After being emailed, the survey remained open for two weeks, with a reminder sent. Amazon gift cards of $100 were raffled to district participants to further incentivize teacher participation during these challenging times. The anonymous response feature disaggregated names from subject data to protect anonymity. A link embedded at the end of the survey enabled teachers to enter the raffle while protecting the anonymity of survey responses. Teachers were protected in this study, informed of the duration of the survey, and provided consent and awareness that participation was voluntary (Appendix 5).

Surveys were completed by 184 teachers and then inspected. Data screening led to the removal of 20 participant data sets, 18 of which has missing parts of survey questions. One survey was omitted as an outlier in which the respondent answered “4” to every question. Another response was omitted because it was the only response indicating no use of a learning management software, deemed an outlier in the current sample. Data analysis for this study thereby included 164 responses.

Note that although the survey included a question asking for teacher reported dedicated technology staff numbers and frequency information, these were omitted from analysis because many participants answered “I don’t know” or left the response blank. Responses varied from 0 to 300, indicating a lack of understanding of the question among teacher participants. FTE-related teacher responses were therefore omitted from analysis. Survey questions were piloted in a small district, where there may have been more teacher awareness and communication with technology leadership, faculty, and staff. Analyses therefore only included the district leader-provided FTE data for each of the categories, originally intended to solely cross-reference teacher data.

Composite Variables

A list of all variables used in the analyses is shown in Table 1. Teacher survey items related to the device, internet, and LMS access were coded into three groups where

0 represents no use/access, 1 represents some use/access and 2 represents full use and access as defined by this study. Items related to LMS were coded individually for analysis. Dedicated technology staff per student ratios were calculated based on Technology Director-reported student enrollment statistics per school and district were used to calculate total dedicated technology faculty and staff per 1000 students.

Likert items taken from the published personalized learning teacher survey (Pane et.al., 2017) were assigned numerical values 1-4 and were averaged by subcomponent following the same item groups as the published study. Subcomponents included the use of a personalized learning plan (PLP), project-based learning (PBL), student centered (SC), student voice (SV) and competency-based assessment practices (CB). A composite personalized learning score, averaging all results, were used in data analysis.

Table 1

Variables Collected via Teacher Survey

Variable	Definition
1:1 Student Device Access	No = 0; Signed Out/In School = 1; Home/School Access = 2
Use of an LMS System	None = 0; Platform used without Grade Pass-back or Parent App = 1; Platform used with Parent Facing Components or Grade Pass-back = 2
Dedicated Technology Staff Per 1000 Students	Number of staff /1000 students Dedicated school FTE teaching and support (non-student)? Dedicated district FTE teaching and support (non-student)? Dedicated school leadership FTE teaching and support (non-student)? Dedicated district leadership FTE teaching and support (non-student)?
High-Speed School Internet Access	No = 0; Sporadic = 1; Reliable = 2
Student High-Speed Home Internet Access	Some Students= 0; Most Students = 1; All Students = 2
Personalized Learning Plans (PLP)*	Characteristics of student learner profiles (Likert scale 1 (not at all) - 4 (a great extent))
Project Based Learning (PBL)*	Extent of project-based learning practices (Likert scale 1 (not at all) - 4 (a great extent))
Student Centered (SC)*	Extent of practices to support goal awareness and progress monitoring (Likert scale 1 (not at all) - 4 (a great extent))
Student Voice (SV)*	Emphasis on student choice and engagement (Likert scale 1 (not at all) - 4 (a great extent))
Competency-Based Assessment (CB)*	Extent of practices to support competency-based learning (Likert scale 1 (not at all) - 4 (a great extent))

Note. The dependent variables denoted with an * come from Pane et al. (2017). The following survey subscales of the teacher survey were omitted due to overlap with variables being studied: technology for personalization, technology curriculum and non-technology curriculum (Pane et al., 2017).

Data Analysis

The five research questions being studied were analyzed separately. Data gathered using Survey Monkey was imported into SPSS and coded by school and district. Descriptive statistics were used to tabulate the percentage of district teachers reporting each level of the respective technology support variable being studied. To answer the first research question, I estimated the following mixed model to assess whether the use of personalized learning varies among teachers within districts and between districts.

$$y_{is} = \alpha_{1s} + e_{is}$$

$$\alpha_{1s} = \beta_1 + u_{1s}$$

$$e_{is} \sim N(0, \sigma^2); u_{1s} \sim N(0, \tau^2)$$

where y_{is} is the aspect of personalized learning being studied (personalized learning plans, project-based learning, student centered, student voice, competency-based assessment) for teacher *i* and district s. Of interest here are the quantities σ^2, an estimate of the variance in the personalized learning among teachers within a district, and τ^2, an estimate of the variance in personalized learning among districts.

To answer research questions two through five, I added a vector of district covariates to the model:

$$y_{is} = \alpha_{1s} + e_{is}$$

$$\alpha_{1s} = \beta_1 + \mathbf{XB} + u_{1s}$$

$$e_{is} \sim N(0, \sigma^2); u_{1s} \sim N(0, \tau^2)$$

where y_{is} is the aspect of personalized learning being studied (personalized learning plans, project-based learning, student centered, student voice, competency-based assessment) for teacher *i* and district s, and **X** is a vector of district technology covariates related to the question of interest. For example, for research question two, this vector included the percent of teachers reporting in-school devices and the percent of teachers reporting home and school devices in the district. Of interest here are the explained variance (R^2) and the coefficients on each predictor. This provides insight into whether technology factors explain between-district variance in personalized learning, and which are the most significant predictors.

CHAPTER 4

This chapter summarizes analyses of the teacher survey results from 27 schools in five Long Island school districts (*N*=164). Teacher reported use of personalized learning was measured using a Likert survey, with responses ranging from 1.00 (not at all) to 4.00 (a great extent). These responses were averaged to yield continuous numeric scores representative of degree of personalized learning used by each teacher, higher values indicate more use of personalized learning. Composites were constructed of overall personalized learning (*M* = 2.77, *SD* = 0.46) and for each subcomponent (Table 2).

Table 2

Descriptive Statistics of Numerical Variables

	Mean	SD	Minimum	Maximum
Personalized Learning (PL)	2.77	0.46	1.82	4.00
Personalized Learning Plan (PLP)	2.58	0.69	1.00	4.00
Competency Based (CB)	2.96	0.69	1.00	4.00
Student Voice (SV)	2.79	0.58	1.20	4.00
Student Centered (SC)	3.43	0.52	1.67	4.00
Project Based Learning (PBL)	2.26	0.72	1.00	4.00

Note. Sample size is 164 for all variables. SD = Standard Deviation.

The highest degree of personalized learning was reported in the subcomponent related to providing student choice (*M* = 3.43, *SD* = 0.52); approximately 70% of respondents reported that they provide a moderate to great extent of student choice in their instruction. In contrast, teachers reported the lowest and most varied degree of personalization in the subcomponent of providing project-based learning opportunities to students (M = 2.26, SD = 0.72).

There was also substantial variation in the technology support variables explored across teachers in the sample. Of the 164 participants, 50.0% reported that their students had access to 1:1 devices both inside and outside of school and 45.1% reported only in-school student 1:1 device access (Table 3). Reliable in-school internet access was reported by 72.7% of survey participants. The majority of teachers surveyed (67.1%) also reported that most students have access to high-speed home, with only 12.8% indicating that all students had access to high-speed internet at home. Learning management software was used by 100% of participants with 59.4% also using grade passback or parent communication features.

Table 3

Descriptive Statistics of Categorical Variables

	N	%
Student Devices		
No Devices	8	4.9
In School Only	74	45.1
Home and School	82	50.0
School Internet		
No School Internet	4	2.4
Sporadic School Internet	41	25.0
Reliable School Internet	119	72.6
Home Internet		
Some Home Internet	33	20.1
Most Home Internet	110	67.1
All Home Internet	21	12.8
Learning Management Software		
No LMS	0	0.0
Student Instruction & Communication	66	40.2
Grade Passback or Parent Communication	98	59.8

Note. Sample size is 164 for all variables.

When analyzed by district, there was substantial variation between and within districts in teacher reported technology support variables (Table 4). For example, 86.2% of participants from District 4 reported students having 1:1 device access both at home and at school, whereas only 9.1% of District 5 participants reported device access at home and at school. District 2 participants all reported reliable school internet access and 46.2% reported that all students have access to high-speed internet at home. In contrast, only 44.8% of participants from District 4 reported reliable school internet and only 6.9% reported that all students have access to high-speed internet at home. District dedicated technology staff ranged from 1.86 to 7.22 full time employees per 1000 students.

Table 4

Descriptive Statistic District Comparisons

	District 1		District 2		District 3		District 4		District 5	
	N	%	N	%	N	%	N	%	N	%
Student Devices										
No Devices	2	2.9	0	0.0	6	19.4	0	0.0	0	0.0
In School Only	36	52.2	3	23.1	11	35.5	4	13.8	20	90.9
Home and School	31	44.9	10	76.9	14	45.2	25	86.2	2	9.1
School Internet										
No School Internet	0	0.0	0	0.0	0	0.0	4	13.8	0	0.0
Sporadic School Internet	17	24.6	0	0.0	5	16.1	12	41.4	7	31.8
Reliable School Internet	52	75.4	13	100.0	26	83.9	13	44.8	15	68.2
Home Internet										
Some Home Internet	14	20.3	1	7.7	6	19.4	7	24.1	5	22.7
Most Home Internet	52	75.4	6	46.2	17	54.8	20	69.0	15	68.2
All Home Internet	3	4.3	6	46.2	8	25.8	2	6.9	2	9.1
LMS										
Student Feedback	29	42.0	7	53.8	12	38.7	10	34.5	8	36.4
Grading or Parent Contact	40	58.0	6	46.2	19	61.3	19	65.5	14	63.6
	M		M		M		M		M	
Tech FTE/1000 Students	2.1		7.2		2.7		1.9		3.0	

Note. N = Frequency; % = Percent; M = Mean.

Research Question 1

A mixed model analysis was used to determine how personalized learning (PL) and its subcomponents vary within and between districts (Table 5). Results showed that most of the variance in personalized learning is within ($\sigma^2 = 0.201$) rather than between ($\tau^2 = 0.012$) districts. Between district variance accounted for less than 6% of the variance observed in the composite personalized learning; this was consistent for all subcomponents, as well. This suggests that the district-level variables explored in the following questions will not strongly related to personalized learning, as there were few differences in personalized learning between districts. However, it suggests that teacher-level variables may explain some of the variance within districts.

Table 5

District Nested Variance of Personalized Learning and Its Subcomponents

	PL	PLP	CB	SV	SC	PBL
Intercept	2.759***	2.570***	2.962***	2.773***	3.424***	2.258***
	(0.062)	(0.093)	(0.076)	(0.069)	(0.046)	(0.057)
σ^2	0.201	0.460	0.471	0.322	0.270	0.524
τ^2	0.012	0.026	0.012	0.013	0.002	0.000

Note. PL = Personalized Learning; PLP = Personalized Learning Plans; CB = Competency-Based Assessment; SV = Student Voice; SC = Student Centered, PBL = Project Based Learning.

Research Question 2

Bivariate mixed model regressions were estimated to determine the predictive power of student device access on personalized learning and its five subcomponents, where personalized learning outcomes were nested in districts. Student device access

(Table 6) was found to account for little between district variance in the personalized learning outcomes, with the exception of the student voice subcomponent of personalized learning (R^2 = 0.62). The percent of teachers reporting school devices or no devices were nonsignificant predictors in all models, suggesting that district device access is not strongly related to teachers' use of personalized learning.

Table 6

Association Between Personalized Learning and Student Device Access

	PL	PLP	CB	SV	SC	PBL
Intercept	2.521	2.321	2.075**	3.219*	3.627*	1.379
	(0.854)	(1.450)	(0.721)	(0.720)	(0.781)	(0.761)
% Reporting School	0.004	0.004	0.012	-0.002	-0.003	0.010
Devices	(0.009)	(0.015)	(0.008)	(0.008)	(0.008)	(0.008)
% Reporting Home &	0.001	0.001	0.007	-0.007	-0.002	0.008
School Devices	(0.009)	(0.015)	(0.008)	(0.008)	(0.008)	(0.008)
σ^2	0.201	0.461	0.470	0.323	0.270	0.524
τ^2	0.015	0.048	0.000	0.005	0.009	0.000
Relative R^2	0.00	0.00	0.00	0.62	0.00	0.00

Note. ***p*<0.01, **p*<0.05. The percent of teachers reporting no school internet was omitted from the regression.

Research Question 3

Regressions were also used to estimate the predictive power of home and school internet access on personalized learning and its five subcomponents. School internet access (Table 7) accounted for a modest portion of the small between district variance in overall personalized learning (R^2 = 0.58), personalized learning plans (R^2 = 0.73) and student centered (R^2 = 0.50), as well as most of variance in student voice (R^2 = 0.92). All variance in project-based learning was observed at the teacher-level, with no between district variation, so the observed R^2 of 0 is mechanical. While the R^2 values suggest that reliable school internet is an important predictor of teachers use of personalized learning, it should be noted that, in all regressions, the coefficient on the percent of teachers reporting reliable internet is nonsignificant. This may be due to the small sample of districts or the limited between-district variability in personalized learning.

Table 7

Association Between Personalized Learning and School Internet Access

	PL	PLP	CB	SV	SC	PBL
Intercept	2.371***	1.917***	2.654**	2.309***	3.180***	2.307***
	(0.223)	(0.307)	(0.350)	(0.225)	(0.208)	(0.279)
% Reporting	0.005	0.009	0.004	0.007	0.003	-0.001
Reliable Internet	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)
σ^2	0.201	0.459	0.471	0.323	0.270	0.527
τ^2	0.005	0.007	0.014	0.001	0.001	0.000
Relative R^2	0.58	0.73	0.00	0.92	0.50	0.00

Note. **p*<0.05. The percent of teachers reporting no school internet or sporadic school internet were omitted from the regression.

When analyzing the relationship between home internet access and personalized learning (Table 8), home internet access was found to account for only a small portion of between district variance in overall personalized learning and personalized learning plans. The coefficient on the percentage of teachers reporting that most or all students have internet access at home was nonsignificant across all regression models. Together, these results suggest that district-average home internet access may not relate to teacher's use of personalized learning.

Table 8

Association Between Personalized Learning and Home Internet Access

	PL	PLP	CB	SV	SC	PBL
Intercept	1.711	0.631	1.945	2.070	2.495**	2.508*
	(0.944)	(1.346)	(1.306)	(1.160)	(0.840)	(1.125)
% Reporting Most or	0.013	0.024	0.013	0.009	0.028	-0.003
All Home Internet	(0.012)	(0.017)	(0.016)	(0.014)	(0.017)	(0.014)
σ^2	0.201	0.460	0.471	0.323	0.012	0.527
τ^2	0.010	0.018	0.014	0.014	0.010	0.000
Relative R^2	0.17	0.31	0.00	0.00	0.00	0.00

Note. ***p*<0.01, **p*<0.05. The percent of teachers reporting some home internet was omitted.

Research Question 4

Deeper use of learning management software accounted for a modest component of the small between district variation observed in composite personalized learning (R^2=0.50). Learning management software use accounted for slightly more of the between district variation observed in personalized learning plans (R^2=0.73). Again, however, the coefficient on the percent of teachers reporting using learning management software for assessment and parent contact was nonsignificant across all models.

Table 9

Association Between Personalized Learning and Learning Management System Use

	PL	PLP	CB	SV	SC	PBL
Intercept	2.196***	1.559*	2.425**	2.397**	2.914***	2.150***
	(0.362)	(0.496)	(0.525)	(0.479)	(0.334)	(0.468)
Assessment	0.014	0.025	0.013	0.009	0.013	0.003
Parent Contact	(0.009)	(0.012)	(0.013)	(0.012)	(0.008)	(0.012)
σ^2	0.201	0.461	0.472	0.323	0.269	0.527
τ^2	0.006	0.007	0.010	0.012	0.000	0.000
Relative R^2	0.50	0.73	0.17	0.08	0.00	0.00

Note. ***p<0.001**p<0.01, *p<0.05. The percent of teachings reporting that an LMS was used for student facing activities was omitted.

Research Question 5

Dedicated technology personnel per 1000 students was analyzed in relation to personalized learning (Table 10). Dedicated full time technology employee per student ratios accounted for little if any of the small between district variation observed.

Table 10

Association Between Personalized Learning and Technology FTE/1000 Students

	PL	PLP	CB	SV	SC	PBL
Intercept	2.651***	2.378***	2.819***	2.715***	3.380***	2.284***
	(0.128)	(0.187)	(0.157)	(0.154)	(0.108)	(0.124)
FTE per 1000	0.035	0.063	0.049	0.019	0.014	-0.010
students	(0.036)	(0.053)	(0.047)	(0.044)	(0.033)	(0.041)
σ^2	0.201	0.460	0.471	0.323	0.270	0.527
τ^2	0.012	0.025	0.012	0.017	0.004	0.000
Relative R^2	0.00	0.04	0.00	0.00	0.00	0.00

Note. ****p*<0.001 and "Omitted" results are described by other levels of the same analysis.

Teacher-Level Analysis

Because of the lack of between-district variance, I additionally estimated a multiple linear regression (without district clustering) to predict teachers overall use of personalized learning (PL) as a function of their self-reported technology variables (indicators of having in school devices, home and school devices, sporadic school internet, reliable school internet, most of the students having internet, all of the students having internet, and LMS usage for assessment and parent communication). The model was not significant, $F(2,161) = .831$, p = .563, and the adjusted R^2 was essentially zero. The estimated coefficients are shown in Table 11. While the indicator for reliable school internet appears to be significant, it should not be overinterpreted given the lack of model significance. Overall, these results underscore those above that showed technology variables may not be strongly related to teachers' use of personalized learning. That said, there are limitations to this work that should be taken into consideration when interpreting the results. Those are discussed in the coming chapter.

Table 11

Multiple Regression Results Predicting Teachers Use of Personalized Learning by Self-Reported Technology Variables

	B	Standard Error	t	*p*
(Constant)	2.133	0.298	7.157	0.000
In School Devices	0.241	0.176	1.37	0.173
Home School Devices	0.233	0.181	1.287	0.200
Sporadic School Internet	0.416	0.253	1.641	0.103
Reliable School Internet	0.507	0.255	1.987	0.049
Most Home Internet	-0.069	0.103	-0.671	0.503
All Home Internet	-0.091	0.15	-0.61	0.543
LMS Assessment Parent	-0.005	0.075	-0.072	0.943

Note. The indicators for "No Devices," "No Internet," "Some Home Internet" and "LMS Communication" were omitted due to collinearity. The FTE per 1000 was omitted because it was only reported reliably at the district level.

Conclusion

Descriptive statistics evidence large differences in student device, internet access, and dedicated technology personnel between districts on Long Island. Trends demonstrate small positive covariance between composite personalized learning and all technology support variables analyzed. However, most of the variance in personalized learning was found within districts, rather than between them. This was true for all subcomponents of personalized learning, and composite personalized learning responses. School internet access and learning management software use accounted for the highest component of the between district variance observed. However, the coefficients on the individual predictors in these models were nonsignificant. Thus, it is difficult to conclusively determine their impact on teachers use of personalized learning.

CHAPTER 5

This dissertation set out to better understand the use of personalized learning strategies among teachers in Long Island, New York. There are three key findings that merit in-depth discussion: (1) There is substantial variability in the technology support factors such as device, internet, and dedicated personnel within and between districts; (2) teachers vary substantially in their reported use of personalized learning; and (3) the use of personalized learning varies mostly within districts, rather than between them.

Implications of Findings

This study revealed inequities both between and within districts in device and internet access, depth of LMS usage, as well as in technology dedicated personnel per students. This raises key concerns about equity of access to resources both within and between districts. Even teachers within the same districts reported different levels of school internet access, suggesting that there may be school-to-school, grade-to-grade, or even class-to-class variability in device and internet access.

When examining between district differences in technology support variables, it is important to note that the five Long Island school districts included in this study diverged in per student expenditure upwards of $8,000 (Ebert & Hildebrand, 2020). The largest percentage of teachers reported unreliable school internet in the lowest funded districts. Similarly indicative of inequities in educational funding, the highest percentage of teachers from the district with the highest per student expenditure reported that most or all students have high speed internet access. The district with the highest per student expenditure also had the highest ratio of dedicated technology personnel per student.

What was striking in this study's findings was the universality of teacher LMS usage. Despite variation within and between schools in student access to devices, internet, and human resources, all teachers reported communicating with students and posting student work using LMS. Most teachers additionally reported using LMS for publishing student grades or communicating with parents. Given that this study was conducted during the COVID-19 pandemic, it is likely that school closures necessitated teachers' adoption of learning management software to communicate with students.

Teacher reported personalized learning varied greatly in the sample. When examining subcomponents, teachers reported the highest degree of personalized learning in student choice and the lowest in project-based learning. Widespread LMS usage may explain findings that the highest degree of personalized learning was reported in the subcomponent related to providing student choice. Teachers self-reported providing students with choices in topic and resources, differentiating resources for students who need remediation or enrichment. Low reported project-based learning opportunities may be attributed to the challenges of COVID-related changes to the school environment. Of all areas of personalized learning, project-based learning may be the most negatively impacted by COVID-related teacher or student absenteeism, the challenges of inconsistent hybrid schedules, and the difficulty of students safely sharing materials and workspaces.

Teacher use of personalized learning and all subcomponents varied more within districts than between districts. The results indicate that variance in personalized learning among teacher participants is dominantly attributed to factors unrelated to current district environments or the models of technological supports included in this study. The small amount of between-district variance could be attributable to limitations of the present study, for example, the small number of districts studied and the selected sample of teachers per district which is discussed later in this chapter. However, it should also be noted that perhaps structural factors affecting teachers (e.g., device access) are school-, rather than district-based.

Relationship to Prior Research

Student access to technology resources has never been more critical than during the COVID-19 epidemic, when schools moved online and in-school students socially distance (Chandra et al., 2020). Findings from this study reveal that a large percentage of students in Long Island may not have access to computers or high-speed internet. If research shows the disproportionately positive impact of 1:1 student device access on students classified as low socioeconomic status before the pandemic (Zheng et.al., 2015), one can assume that the potential impact of district device access would be even greater on students of low socioeconomic status throughout the past year of digital learning.

This study suggests that neither between nor within district gaps in technology access on Long Island have been closed by state initiatives like Smart Bond nor federal initiatives like eRate (Smart Schools Bond Act, 2014). Both New York State Smart Bond and federal eRate grants may continue to fall short of their goals because they are structured as reimbursements, requiring districts to pay for material and labor up-front with waits up to 6 months for reimbursement (Smart Schools Bond Act, 2014). High need districts need to take out loans before starting the already cumbersome state and federal application processes. In fact, eRate only retroactively reimburses a maximum of 50% of connectivity projects (Federal Communication Commission, 2020). Combine that with a world-wide shortage of mobile devices (Chandra et al., 2020), the structure of federal and state aid for connectivity may not sufficiently support students in high-need districts, especially during a pandemic. This shortcoming may explain the large within and between district variability in technology resources observed during this study.

Despite diverse findings regarding student device access and school internet access, participants in this study all reported using LMS to communicate with students, assign work, and provide feedback for learning. Prior studies on LMS adoption found that the perceived usefulness of the LMS was the most important factor teachers considered in using its features (Stockless, 2018) (Wraikat et al., 2017), with years of teacher use related to frequency and depth of use (Lonn & Teasley, 2009). COVID-19 related stay at home orders and immediate digital learning needs may have motivated teachers to adopt and use LMS at a rate and depth far beyond that observed prior to the pandemic (Laho, 2019). Teachers all quickly adopted LMS, which likely improved ease of communication and grading.

While essential for remote learning, LMS usage appears to have been a technical change related to productivity, not necessarily correlating with changes in teacher practice required to further personalized instruction (Bebell and Kay, 2010). With increased familiarity and use, LMS makes it easy for teachers to target enrichment and remediation materials to specific students and to allow for choices via interactive online materials (Dagger et al., 2007). Universal LMS adoption and the diversity of COVID back-to-school plans, including hybrid instruction, may explain why teachers reported providing the highest degree of personalized learning in the subcomponent student choice.

Universal LMS adoption evidences the increased use of technology in our schools. Yet, this universality of technology did not equate with high levels of reported personalization, except in the subcomponent of student choice. In fact, in terms of project-based learning, teachers in this study reported an average degree of personalized learning of 2.26 on a 1.00-4.00 scale, whereas the published study on which it is based reported an average of 2.32 (Pane et al., 2017). Findings from this study suggest that implementation of personalized learning is independent of technology access or use at the district level.

As the history of technology and educational changes teaches us, “simply having access to computers and learning to use them as tools is only part of the story of the educational use of computers” (Tyack & Cuban, 1995, p 125). Reliable technology may be a foundational pre-requisite or a catalyst to implementing personalized learning (Bingham, et al., 2018). District-wide professional development towards personalized learning or student-centered learning environments may be best supported by technology, but technology alone was not found to significantly impact instruction. That said, the district-level technology factors may not be sufficiently proximate to teachers to truly mediate their use of personalized learning. Focus should be given to variability among schools in these factors or even variability within buildings.

Limitations of the Study

The most significant limitations in this study were related to sample size at both the teacher, school, and district levels. The original intent of this study was to focus on school-based differences in technology and personalized learning; not district-based comparisons. This study was rooted in literature that used schools as the unit of study

(Bingham et al., 2018, Steiner et. al, 2015, Pane et. al, 2017, Lee et al., 2018a). Insufficient school sample sizes limited the statistical significance and power of school-based analysis. District data included elementary, middle, and high schools, possibly masking significant between school differences in personalized learning. Because of the small sample of districts, the covariates were highly correlated, and many were collinear. Since there were only five districts included in this study, there also were insufficient degrees of freedom to include more than two predictors in the model. Multiple regression analysis suggested that regardless of the limited sample size included in this study, technology supports and respective models of such appear to be unrelated to personalized learning.

Data was collected during the COVID-19 global pandemic, while teachers are engaged in remote, hybrid and/or in-person learning, thereby limiting the generalizability of the study chronologically. Unique circumstances and the associated technological demands may have impacted the way in which teachers answered questions related to both technology and personalized learning. There may also be significant bias in district selection, as participants were acquired through the researcher's personal professional contacts. District, school, and teacher self-selection for study participation may further bias survey results, favoring those who may value or devote resources to technology having greater interest in being a part of the study.

Recommendations for Future Research

Four areas of future research are recommended to expand on the findings of this study; 1) collaborative/action research to yield larger sample size for more generalizable findings 2) analysis of socioeconomic and racial trends in student technology access 3) mixed methods analyses of personalized learning and technology and 4) case studies of exemplars of personalized learning.

Repeating this study in coordination with more district technology directors could potentially yield higher school-based participation rates enabling school level analysis. School based analysis would have less grade-based and leadership-based variation. Increased participation in the study would enable the hierarchical analysis originally planned to test the conceptual framework of this study.

This study reveals the urgent need for more school, district, academic, and policy-related research on student device, school, and home internet access on Long Island. Specifically examining technology access and use, as well as personalized learning by both socioeconomic status and race would further improve our understanding of inequities facing Long Island's disparate learning communities (Golob et al., 2018). As teachers attempted to meet student needs remotely, this study shows that many students on Long Island cannot access resources easily while others can. Variation in access to learning found within and between districts merits study by school, grade, socioeconomics, and race. Research on personalized learning by school, grade, socioeconomics and race would provide further data on related inequities between and within districts.

Analyses suggest that variables outside of devices, internet, LMS access and human resources may have a more significant impact on personalized learning than these technological investments made by districts. Qualitative investigation of these questions via teacher and/or leader interviews, and an extensive review of state technology plans, budgets and grant proposals may have further informed and contextualized research findings from this study. For example, interviews with stakeholders could reveal nuanced obstacles to personalized learning that statistical findings could not. While technological access has been an obvious area of concern and research, further research must also be done on how students can remain at the center of learning.

It is important that educators and researchers do not confuse software-based individualization of learning with personalized learning. Responsive software may provide individualized feedback or levelled challenges but falls short of empowering students with authentic learning. Software does not enable students to engage in co-creation, self-discovery, and social construction.

Pandemic-related increases in dropout rate and absenteeism reveal the need for more research on the systemic operationalization of personalized learning. Further investigation into specific subcomponents like student voice or project-based learning may provide opportunities to better inform instructional, district and regional shifts to put students at the core of educational decisions. Case studies of schools implementing high levels of personalized learning could fine-tune personalized learning surveys and metrics to better assess student voice, co-creation, social construction, and self-discovery.

Recommendations for Future Practice

Findings from this study inspire three recommendations for future practice; 1) government educational technology funding must be revamped to achieve espoused equity goals 2) district funding of professional development towards personalized teacher instruction are as important or even more important than educational technologies in achieving personalized learning and 3) districts need to position themselves to differentiate and selectively implement only those technologies that further goals for student learning.

Enduring disparities in access evidence a need for federal and state educational technology funding schemes to change. Less resourced districts continue to endure long waits for funding that need to be paired with financing plans and coordinated district spending. This is not conducive to timely investments in infrastructure or user-end investments. For example, it would benefit schools to support cloud-based network solutions, software, and professional development in a timely pro-active manner. These investments, in addition to student home internet access initiatives, are not permitted for us in federal eRate or state Smart Bond investments. Less restrictive funding programs, that could evolve and support the ever-changing demands on educational technology, would better support closing gaps in district access.

Statistical analyses from this study implies that technology is not preventing teachers' implementation of personalized learning. Technology remains solely a tool through which to enable student voice, co-creation, social construction, and self-discovery (Kallick & Zmuda, 2017). Computer-based programs that individualize learning can be a resource in building student skills using responsive technologies but should not be confused with personalized learning. Personalized learning empowers students through authentic learning. If, as this study suggests, technology is not related to personalized learning, perhaps resources being funneled into software, hardware, or connectivity in the name of personalized learning could be better spent on other initiatives. For example, student or community centered programs, projects, or schools may better empower students regardless of student technological access.

While technological access for all is being pursued by the state and federal government, there should be a systemic focus on the federally stated goal of personalized learning. For example, professional development should support personalized student learning goals instead of focusing on a particular software or product. Educational technology companies' goals are financial profit, whereas instructional technology goals should remain product agnostic. Teacher instructional practices, not the tools they use, need to remain at the core of our focus of our work in educational technology. This study reinforces that teacher personalized learning practices are independent of technology access. Focused district learning on student voice, co-creation, social construction and self-discovery are necessary to achieve personalized learning, regardless of what tools a district provides.

Conclusion

Data exposed large inequities in student device and internet access both within and between districts at a time of dependence on digital learning. This study also found a high level of variability in personalized learning both within and between districts unrelated to technological access. Findings suggest congruence with prior studies that evidence the limitation of technical tools in changing instruction. While limited by sample size and uniquely implemented during the COVID-19 pandemic, this study reveals the technical and adaptive challenges faced by teachers in personalizing student learning.

APPENDIX 1

St. John's University Institutional Review Board Approval

From: irbstjohns@stjohns.edu <irbstjohns@stjohns.edu>
Sent: Monday, December 14, 2020 9:17 AM
To: Erin Fahle <fahlee@stjohns.edu>; janna.ostroff17@stjohn.edu <janna.ostroff17@stjohn.edu>
Subject: IRB-FY2021-236 - Initial: Initial - Exempt - St. John's

ST. JOHN'S UNIVERSITY

Federal Wide Assurance: FWA00009066

Dec 14, 2020 9:17:20 AM EST

PI: Janna Ostroff
CO-PI: Erin Fahle
Dept: Ed Admin & Instruc Leadership

Re: Initial - IRB-FY2021-236 *The Landscape of Personalized Learning in Long Island Schools*

Dear Janna Ostroff:

The St John's University Institutional Review Board has rendered the decision below for *The Landscape of Personalized Learning in Long Island Schools*.

Decision: Exempt

PLEASE NOTE: If you have collected any data prior to this approval date, the data must be discarded.

Selected Category: Category 2.(i). Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey p
recording).
The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or t

Sincerely,

Raymond DiGiuseppe, PhD, ABPP
Chair, Institutional Review Board
Professor of Psychology

APPENDIX 2

Researcher Created Teacher Survey Items

1. Which best describes our classroom(s):
   a. No school/district computers, tablets or iPads are available for my students' use
   b. Computers, tablets or iPads can be signed out for my students' use
   c. All students are provided a computer, tablet or iPad for in-class use
   d. All students are provided a computer, tablet or iPad for in-class and home use

2. Which best describes your classroom(s):
   a. There is no high-speed internet access
   b. There is sporadic high-speed internet access
   c. There is reliable high-speed internet access

3. Which best describes your students' access to high-speed internet at home:
   a. Some of my students have access to high-speed internet at home
   b. Most of my students have access to high-speed internet at home
   c. All students in my class(es) have access to high-speed internet at home

4. On which, if any, platform or Learning Management System do you post classroom content and/or assignments for your students?
   a. I do not use any 2-way platform to assign or collect work (0)
   b. Google Classroom
   c. Seesaw
   d. Schoolology
   e. Canvas
   f. Edmodo
   g. Moodle
   h. Pearson SuccessNet
   i. Hiaku
   j. Blackboard
   k. Other

5. If so, indicate if you use the LMS to do the following (Yes/No):
   Post assignments
   Communicate with students
   Collect assignments
   Provide feedback to students about work submitted
   Provide summative grades/assessment data to students
   Publish/share student work with parents
   Communicate with parents
   Provide grades/assessment data to parents

6. Which of the following best describe the frequency with which you requested support with educational technology throughout this past calendar year:

Technical Support	0	1	2	3	4+
Usage	0	1	2	3	4+
Pedagogical Support	0	1	2	3	4+

To the best of your knowledge, how many of the following categories of faculty/staff are dedicated to support faculty use of computer technology (if part-time or stipend-based, provide your best-estimate of fraction of non-student-contact time or time dedicated to technology ex: 1.25, 4.5).

7. School Instructional Technology Teacher on Special Assignment, Teacher Coach or Teacher Trainer (Exclude primary student-contact responsibilities from the estimate)
8. District Instructional Technology Teacher on Special Assignment, Teacher Coach or Teacher Trainer
9. School-Based Technical Support (computer/network technicians): .25, .5, .75, 1, 1.25, 1.5, 1.75...
10. District-Based Technical Support
11. School-Based Computer Clerical/Computer Lab TA or Monitor(s)
12. District-Based Computer Clerical/Computer Lab TA or Monitor(s)
13. School Administrative Leadership Roles Dedicated to Technology
14. District-Administrative Leadership Roles Dedicated to Technology

The following items were RAND Teacher Survey Items (Pane et al, 2017)

15. Do your school's learner profiles or learning plans have these attributes? 1 (not at all); 4 (a great extent)
    a. Exists for every student.
    b. Are frequently updated to incorporate new information.
    c. Summarize the student's strengths, weaknesses, and progress, drawing on multiple sources of information, including standardized tests and other information.
    d. Summarize the student's goals, interests, and aspirations.
    e. Set forth a personalized plan for students to accomplish instructional goals. Are routinely accessed/updated by teachers.
    f. Are routinely accessed/updated by students.
    g. Are routinely accessed/updated by parents or guardians.

16. Please indicate the extent to which each of the following statements describes your curriculum and instruction. 1 (not at all); 4 (a great extent)
    a. I assign projects that extend over several weeks or months.
    b. I assign projects that are interdisciplinary (e.g., combining science and literature).
    c. Students have opportunities to provide input into the design and focus of project work.
17. Please indicate the extent to which each of the following statements describes your curriculum and instruction. 1 (not at all); 4 (a great extent)
    a. I clearly present the goal or objective for each assignment.
    b. I have devised strategies that allow students to keep track of their own learning progress.
    c. When students are working on an assignment or activity, they know what the goals of the assignment or activity are.
18. Please indicate the extent to which each of the following statements describes your curriculum and instruction. 1 (not at all); 4 (a great extent)
    a. I require students to show that they understand a topic before they can move on to a new topic.
    b. Different students work on different topics or skills at the same time.
    c. I give students the chance to work through instructional material at a faster or slower pace than other students in this class.
    d. Students have opportunities to review or practice new material until they fully understand it.

19. Please indicate the extent to which each of the following statements describes your curriculum and instruction. 1 (not at all); 4 (a great extent)
    a. Students have opportunities to choose what instructional materials (such as books or computer software) they use in class.
    b. Students have opportunities to choose what topics they focus on in class.
    c. I provide a variety of materials or instructional approaches to accommodate individual needs and interests.
    d. I connect what students are learning with experiences they have throughout the rest of the school day or outside of school.
    e. I frequently adapt course content to meet students' needs by providing additional assignments, resources, and activities for remediation or enrichment.

APPENDIX 3

Permission to Modify and Use Survey

Re: Personalized Learning Instructional Staff Survey Results

You replied on Mon 10/15/2018 6:15 PM

OJ Ostroff, Janna
Tue 10/9/2018 4:38 PM
To: Steiner, Elizabeth <esteiner@rand.org>

Dear Dr. Steiner,

Thank you! This is very helpful to me. With permission and attribution, I would like to use parts of your survey to evidence the validity of a survey I am using first in a mini study of my own district and then potentially in my dissertation.

Janna Ostroff
K-12 Supervisor of Science and Technology for Instruction
Oyster Bay-East Norwich Schools
516-624-6544

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twitter bird (249x202) (20x16) twitter.com/OBENSchools

RE: Personalized Learning Instructional Staff Survey Results - Microsoft Edge

outlook.office365.com/owa/?ItemID=AAMkADgwYjA0OGVjLTFjNWEtNDE2Mi1iY2JkLWM4YzMxNzA5MDA1ZgBGAAAAAABZ91ok

Reply | Delete Junk | •••

RE: Personalized Learning Instructional Staff Survey Results

SE Steiner, Elizabeth <esteiner@rand.org>
Mon 10/1, 8:56 AM
Ostroff, Janna

Reply |

You replied on 10/9/2018 4:38 PM.

Hi Ms. Ostroff,

Please find an updated version of the survey, and related report, at this page:
https://www.rand.org/pubs/research_reports/RR2042.html

You are welcome to use the survey questions at the link above, or cite our findings, with attribution.

Sincerely,
Elizabeth

From: Ostroff, Janna [mailto:JOstroff@obenschools.org]

APPENDIX 4

Online Survey Consent Form

You are being invited to participate in a research study titled "The Landscape of Personalized Learning in Long Island, New York." This study is being done by Janna Ostroff from St. John's University. You were selected to participate in this study because you are a K-12 teacher in a Long Island public school.

The purpose of this study is to explore variation in personalized learning in Long Island and how it relates to technological device access and infrastructure. It is intended to inform technology planning and budgeting for personalized learning during and beyond the COVID crisis.

If you agree to take part in this study, you will be asked to complete an online survey about your planning and instruction that will take approximately 12 minutes to complete.

There are no known risks to participating in this study. As with all research, there is a chance that confidentiality could be compromised; however, we are taking precautions to minimize this risk.
Participant names and email addresses will be collected and stored in a separate file from survey responses. The names of individuals, participating schools, and participating districts will not be used in this study.
In each district with at least 33 participants, a $100 Amazon Gift card will be raffled and sent upon the close of the survey response window.
If you have questions about this project or if you have a research-related problem, you may contact the researcher, ***[Janna Ostroff, 917-596-4953]*** If you have any questions concerning your rights as a research subject, you may contact the St. John's University Institutional Review Board *[**irbstjohns@stjohns.edu**]*
By clicking "I agree" below you are indicating that you are at least 18 years old, have read this consent form and agree to participate in this research study.
Please print a copy of this page for your records.

I Agree	I Do Not Agree

APPENDIX 5

FTE Data Collection Spreadsheet

School Name	Current Enrollment			
	District-Wide Technology FTEs			
	Tech Coach/Teacher Trainer/Specialist	Computer/Network Technician	Clerical/TA or Monitor	
FTE's				
	School Technology FTEs (excluding all student contact/instructional)			
School	Tech Coach/Teacher Trainer/Specialist	Computer/Network Technician	Clerical/TA or Monitor	Administrative Leadership

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