SURVEY OF TEACHER OPINIONS ON THE USE OF LEARNING ANALYTICS TO IMPROVE STUDENT LEARNING

A Dissertation
by
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Abstract

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This investigation focused on the responses of K-12 teachers from North Carolina regarding their opinions about awareness, usage, resources, and attitudes concerning learning analytics. While corporations such as Amazon, Facebook, Google, and Apple inspired numerous imitators throughout the business world, educational institutions began to adapt already proven and successful analytics practices to improve education. In the past several years, learning analytics has become a buzzword that progressive members of the education community use with increasing frequency to describe data-driven strategies for improving learner outcomes. As early as 2013, the Horizon Report estimated that learning analytics would be widely adopted in K-12 classrooms within three years. Teacher opinions contribute to the evaluation of the validity of the 2013 Horizon Report predictions for implementation of learning analytics in K-12 schools as well as document the role of teachers in the adoption of learning analytics in the classroom. The voice of the teacher, a major stakeholder in the implementation of innovation in K-12 classrooms, is heard.

Using a conceptual framework based on exploratory research, within the context of evidenced-based decision-making, an online survey composed of 32 fixed-response items was used for data collection via the Qualtrics platform. While the literature does provide numerous articles on the possibilities of using learning analytics in K-12 classrooms, the voice of the

teacher in how the innovation is being implemented can be heard through the use of a survey methodology that looks across respondents on issues and subsequently compares the responses of teachers representing different school settings and having different educational and professional experiences.

This study of teacher impressions of learning analytics at the K-12 level in North Carolina is disheartening considering the amount of literature and products that have been generated over the past decade. Likely, many K-12 teachers in North Carolina have heard the buzzword, have reviewed products and strategies related to learning analytics, and have acquired many relevant technical skills, but they have not gained a cohesive overview of the potential of the concept. The literature review revealed that the concept of learning analytics is seen with much favor yet is associated with frustration over implementation. Survey respondents did reveal some awareness and usage of learning analytics, in some cases did have access to support personnel and other resources, and did reveal a very positive attitude toward the concept. However, much confusion exists on the specificities of learning analytics and results provided little insight in any systematic implementation of the strategies at either the school or district levels. Haphazard adoption along with inconsistent leadership and varied funding can lead to inequities across districts and eventually to abandonment of a seemingly worthy educational innovation. Additional studies are needed in the K-12 sector to establish the worth of data-driven ways to improve classroom instruction, determine how to improve training for teachers in the use of data, and to support innovation.

Acknowledgements

I have received a great deal of support and assistance throughout the writing of this dissertation. First I would like to thank my supervisor, Dr. Les Bolt and the other members of my committee, Dr. Mina Min and Dr. Trent Spaulding. Their guidance and recommendations have been instrumental to the completion of my project. Dr. Vachel Miller, the director of the doctoral program, one of my first professors in the program, has been a constant source of support and inspiration.

As a teacher, who has worked with elementary, middle, and high school students in public schools over a span of 13 years, I want to dedicate my small contribution to the future of education to the precious students whom I have had the honor of teaching and to the dedicated colleagues with whom I have had the privilege of working. Further, I dedicate my work to the innovative professors who inspire teachers to make a difference.

Last, this journey would not have been possible without the unwavering support of my husband, Matthew Baldwin, and my parents, George and Margot Olson.

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Chapter 1: Introduction

No citation is needed to state the obvious that public education of the nation's children is geared toward adopting available and appropriate resources to enable children to reach their potentials and succeed as contributing citizens. All children, regardless of economic status and geographic location, deserve the best of available resources to facilitate growth and development, not as disenfranchised or marginalized citizens, but as individuals fully capable of realizing their potentials. With the continuing and accelerating introductions of new technologies across societies, adaptations for use in school systems are a constant and possibly overwhelming challenge for educators. Consider that some innovations of the past have survived the test of time whereas others have not. For example, advances in school record keeping and registrations via the use of computerized accounting systems provide student information for immediate use by teachers in their tasks of attempting to provide appropriate learning strategies for each student. On the other hand, the upheaval in the design of classrooms via the open-plan strategy for individualized instruction did not succeed in meeting the needs of most students. What innovations have potential and which can survive the challenge of actually improving teaching methodologies? Currently, following the models of big data in general and data mining in business contexts, learning analytics has emerged as an innovation across all education sectors (Aiden & Michael, 2014).

While corporations such as Amazon, Facebook, Google, and Apple (Miguel & Casado, 2016) inspired numerous imitators throughout the business world, educational institutions began to adapt already proven and successful analytics practices to improve education and drive curriculum (Davenport & Dyché, 2013). In a time of decreasing budgets and increasing expectations, education institutions are looking at how businesses have used data and analytics to increase profits and improve customer satisfaction (Henchsen, 2014). In the past several years, learning analytics has become a buzzword that progressive members of the education community use with increasing frequency (Campbell et al., 2007). With fully established systems of learning analytics in place, every student could have an individualized education plan that updated in real time, teachers could have instantaneous access to gaps in their daily curricula, and districts could allocate their limited funds to needed areas.

The data collected in education settings today goes beyond traditional data sets that are associated with schools. While traditional records, such as transcripts and health files, remain viable, students leave behind much more. With the increase of technology in the classroom, students provide data trails with every keystroke, click of a mouse, or use of a smartphone. Software programs, online programs, online classes, web research, e-readers, and smart devices are capable of recording every move a student makes. This information has the potential to allow researchers to discover numerous new ways that students are learning and disseminating information (Siemens, 2013).

Business analytics has had a massive impact on strategies used for marketing products and services across the globe. Through the compilation of data, information can be provided to consumers as they search for specific products, both as individuals or as persons with specific profiles, and can influence the outcomes of their choices. Personal spending habits and specific interests of consumers are used to specify products and services that will meet individualized needs. So, why not use a similar strategy to help teachers provide the type of personalized approach that will adapt instruction for each student? Consider the following synopsis provided by the 2013 Horizon Report for K-12 education (Johnson et al., 2013).

> Learning analytics is education's approach to "big data," a science that was originally leveraged by businesses to analyze commercial activities, identify spending trends, and predict consumer behavior. The rise of the Internet drove research into big data and metrics as well as the proliferation of web tracking tools, enabling companies to build vast reserves of information they could study and leverage in their marketing campaigns. Education is embarking on a similar pursuit into data science with the aim of improving student retention and providing a high quality, personalized experience for learners. Learning analytics research uses data analysis to inform decisions made on every tier of the educational system. Whereas analysts in business use consumer data to target potential customers and personalize advertising, learning analytics leverages student data to build better pedagogies, target at-risk student populations, and assess whether programs designed to improve retention have been effective and should be sustained—outcomes for legislators and administrators that have profound impact. For educators and researchers, learning analytics has been crucial to gaining insights about student interaction with online texts and courseware. Students are beginning to experience the benefits of learning analytics as they engage with mobile and online platforms that track data to create responsive, personalized learning experiences. (p.20)

In the 2013 Horizon Report for K-12, the time until adoption of learning analytics was listed as two-to-three years. Subsequent Horizon Reports have also listed similar timelines for implementation of learning analytics (Freeman et al., 2017; Johnson et al., 2014).

Problem Statement

At present, considerably more time for implementation of learning analytics across school settings has passed than was predicted by the 2013 Horizon Report. The question then arises about the validity of the prediction across the student populations of specific demographics and the role of teachers in the process of adoption of learning analytics in the classroom. Learning analytics is found in education at the micro-level in classrooms and departments through the macro-level in national or international research projects (Siemens, 2013). Teachers can use the information generated by online teaching programs to make instant adjustments to a student's curriculum while researchers can look at data from a student population that crosses state and even national borders.

Despite becoming a recognizable term with positive associations in current educational research and literature, how and to what extent teachers are regularly using learning analytics is still unclear (Michos et al., 2020). The purpose of this study is to collect self-reported data on teachers' experiences with learning analytics in the classroom. Has learning analytics in the K-12 context advanced, stalled, or stagnated? Results of the study will contribute to answering the question of the validity of the Horizon Report predictions for implementation of learning analytics in the K-12 classroom (Freeman et al., 2017; Johnson et al., 2013; Johnson et al., 2014) as well as document implementation of learning analytics across student populations representing varied demographics and the role of teachers in the process of adoption of learning analytics in the classroom.

Research Questions

The following four research questions focus on an investigation of the status of teacher awareness, usage, resources, and attitude in regard to learning analytics.

1. Across total respondents and within selected subgroups of respondents, what is the level of *awareness* by K-12 teachers of learning analytics as a viable strategy to improve instruction?

2. Across total respondents and within selected subgroups of respondents, how have K-12 teachers shown *usage* of learning analytics themselves or observed others using learning analytics as a viable teaching strategy to improve instruction?
3. Across total respondents and within selected subgroups of respondents, what types of *resources* have been available to K-12 teachers for gaining skill in using learning analytics as a viable strategy to improve instruction?
4. Across total respondents and within selected subgroups of respondents, what are K-12 teacher *attitudes* about the potential or actual use of learning analytics as a viable strategy to improve instruction?

The four research questions provide a progression of teacher opinions from awareness of the concept presented in the literature, to consideration of usage of the concept in practice, to resources for facilitating implementation of the concept in the classroom, and finally to a personal judgment of the viability of the concept in educational practice. Using comparisons of responses from varied demographic characteristics (e.g., size of school district) will further provide descriptive input about the use of learning analytics in K-12 classrooms.

Methodology

To examine the opinions and experiences with learning analytics of K-12 teachers, a quantitative methodology, using descriptive results from a survey instrument, provided a viable approach for gathering information about involvement of a group of individuals with a specific issue. According to Fraenkel and Wallen (2006), survey "researchers are often interested in the opinions of a group of people about a particular topic or issue. They ask a number of questions, all related to the issue, to find answers" (p. 397). Best and Kahn (1998) have indicated that "in analyzing political, social, or economic conditions, one of the first steps is to get the facts about the situation or a picture of conditions that prevail or that are developing" (p. 116). Gall et al. (2003) have simply defined survey research as "use of questionnaires or interviews to collect data about the characteristics, experiences, knowledge, or opinions of a sample or a population" (p. 638). While the literature does provide numerous articles on the possibilities of using learning analytics in K-12 classrooms (Cech et al., 2015; Cech et al., 2018; Joksimovic et al., 2019; Maseleno et al., 2018; Michos et al., 2020), the voice of the teacher in how the innovation is being implemented can be heard through the use of a survey methodology that looks across respondents on issues and subsequently compares the responses of teachers representing different school settings and having different educational and professional experiences.

Significance of Issue

Learning analytics is receiving attention in the domain of education. Consider *The Journal of Learning Analytics,* established in 2011, and the International Conference on Learning Analytics, first held in 2011; both have evolved in a very short time to provide a platform for the dissemination and the adoption of the practice. Furthermore, many companies with prominent names (Couture, 2018), like Pearson Education and Renaissance Learning, or even small start-ups, like No Red Ink and Junyo, are entering the marketplace to provide software and training for implementing learning analytics. As more and more learning environments migrate to an online model, use of learning analytics to evaluate efficacy of different education programs is becoming easier. Learning analytics is used to enhance the experiences of both learners and educators with both often happening simultaneously. Panorama Education and BrightBytes are two such examples that offer their products on a software as a service (SaaS) platform.

However, data documenting the breadth of the implementation of learning analytics across varied demographics is lacking; but, perhaps, even more critical is the lack of information about the exposure of classroom teachers in K-12 education in regard to the use or even the possibilities of use. Dellinger (2019), in fact, concluded from his research that "while there has been a growth in research on the adoption process in higher education context, little has taken place in K-12" (p.ii). According to Michos et al. (2020), "one approach to understanding the impact of LA tools and their practical implementation in primary and secondary educational contexts is to involve stakeholders" (p. 94) including teachers.

The study is significant in that it examines the prediction published about learning analytics by the K-12 edition of the Horizon Report (Freeman et al., 2017; Johnson et al., 2013; Johnson et al., 2014), a widely known and respected educational resource for decision-making by educational stakeholders. Focusing on the opinions of teachers, in regard to such variables as awareness, usage, resources, and attitude, is particularly relevant to documenting levels of adoption of the innovative technology within the K-12 classroom.

While the business world has been experimenting with and honing their use of analytics to drive business decisions, education has had a later start. In large part, the late start can be attributed to the differences in capital. Material goods are the capital in business while people are the capital in education. Before learning analytics can be used to its full potential, a proper infrastructure must be in place. Sources of data need to be identified, storage for the data needs to be created, educators need to learn how to use and interpret the data, and algorithms to interpret the data need to be created. Analytics goes far beyond the printouts of data that educators are often tasked with using today. An infrastructure should be in place that allows for real-time updating of information provided to students, educators, and administrators. By having constant feedback, students can self-monitor what they have mastered and what they still need to learn. Real-time updates will also enable teachers to adjust curriculum at an individual level for different students. Administrators can identify trends and plan accordingly. Few empirical studies have been published that investigated adoption of learning analytics in K-12 settings and even more absent has been the voice of the teacher. A survey that describes awareness, usage, resources, and attitude of K-12 classroom teachers is one small, but significant step in furthering research about the possibility of learning analytics becoming a successful innovation in public schools.

Definition of Terms

Analytics got its start as data science. Statisticians have long been making sense out of numbers; advances in technology provided opportunity for collecting and storing massive amounts of data. From this union, analytics was born (Bryant et al., 2008; Davenport et al., 2007; Davenport, 2013; Davenport & Harris, 2009). Throughout the 1960s and 1970s, statisticians found themselves developing the computer skills necessary to use new technologies to make sense of the larger and larger sets of data being collected. The 1980s saw the emergence of enhanced computational power to analyze data using traditional statistical methods. In the 1990s, *business analytics* emerged as businesses began realizing that they could use the data being collected about consumers to make decisions that would yield larger profits (Miguel & Casado, 2016). The online revolution of the early 2000s saw businesses using their websites to collect data to help direct consumers to purchase more. Towards the end of this century's first decade, educators began to realize that business analytic practices could be used to make decisions and understand the processes of learning. Throughout the second decade, *learning analytics* has become part of the education lexicon. Educators are tasked with data-driven decision-making, and a definite movement exists to make learning analytics accessible to more K-12 classrooms (Davenport & Dyché, 2013; Joksimovic et al., 2019).

Learning analytics is a new way of collecting information about students that has garnered great interest during the decade of 2010. For example, during the 1st International Conference on Learning Analytics and Knowledge in 2011, learning analytics was defined as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for understanding and optimizing learning and the environments in which it occurs" (1st International Conference on Learning Analytics and Knowledge, 2011, para. 6). A subsequent definition, provided by the Centre for Educational Technology & Interoperability Standards, emphasized a more practical use of education data by stating that "analytics is the process of developing actionable insights through problem definition and the application of statistical models and analysis against existing and/or simulated future data" (Cooper, 2012, p.3).

Education institutions have recently realized the potential of using the massive amounts of data collected about students to make better predictions on how to best achieve student success. "As the quantity of data has increased, the attention of researchers, academics, and businesses has turned to new methods to understand and make sense of that data" (Siemens, 2013, p. 1381). There is a "perfect storm" brewing in education institutions for learning analytics; the demand for data is growing, as is the supply of data. As schools face greater accountability, administrators are going to be relying more and more on data (Verbert et al., 2012). "LA promises to bring new insights into the learning process to enable practices that enhance student success" (Dawson et al., 2019, p. 446).

Organization of Study

Following the overview of the context for the study presented in Chapter 1, remaining chapters include a review of literature on learning analytics; a description of the methodology used to gather opinions of classroom teachers about learning analytics; results of a survey of opinions on learning analytics;, and finally, conclusions based on interpretation of survey results. The literature review, provided in Chapter 2, includes classic literature highlighting development of analytics within the context of education; research literature reporting studies of learning analytics primarily within the context of K-12 classrooms; and a conceptual framework for the gathering, analysis, and interpretation of survey data from K-12 teachers. An overview of the methodology, provided in Chapter 3, covers the procedures used to collect data for the investigation and includes not only participants, instrumentation, data collection and analysis but also the role of the researcher in the investigation, ethical issues, and trustworthiness of findings. Chapter 4 provides tables of results from the survey items. Finally, Chapter 5 provides discussion of results in the context of implications, policy, and practice as proposed by the Horizon Reports.

Chapter 2: Literature Review

The average amount of data collected per person each year is staggering, and the amount amassed by the entire population is unfathomable. In *Uncharted: Big Data as a Lens on Human Culture*, Aiden & Michael (2014) reported:

> The average person's data footprint—the annual amount of data produced worldwide, per-capita—is just a little short of one terabyte. That's equivalent to about eight trillion yes-or-no questions. As a collective, that means humanity produces five zettabytes of data every year: 40,000,000,000,000,000,000,000 (forty sextillion) bits. (p.11)

Understanding the enormity of such a number is nearly impossible, but Aiden and Michael (2014) do offer some perspective. If you wrote out the ones and zeros contained in the data for a megabyte, your writing would be able to climb Mount Everest five times. Five zettabytes written out by hand would easily make it to the center of the Milky Way. These estimates are for the year 2013, and, as the authors point out, the amount of data produced at least doubles every year.

Data from education come from many different sources. Students typically generate data spanning a 13-year period. Teachers accumulate data spanning their entire careers. Institutions compile data spanning their entire existence. Being able to harness these data to help understand what works in education is of key importance. Furthermore, data are being used in two distinct ways in the realm of education. The first, which is referred to as learning analytics, is focused on individual learners and creation of optimum scenarios for success through use of data to drive decision-making in curriculum planning (Boghossian, 2006). The second approach, sometimes differentiated from learning analytics as academic analytics, uses data on an institutional scale to drive policy decisions to create schools that provide the optimum learning environment for students (Goldstein & Katz, 2005). Learning analytics can be used to drive curriculum at the micro-level for individuals, and academic analytics can be used at the macro-level to drive curriculum on an institution or district-wide level (Siemens, 2013). An overview of the development of learning analytics, a focus on K-12 implementation of learning analytics, and a conceptual context for surveying teachers in regard to learning analytics follows.

Classic Literature

Having gone from fad to trend to accepted practice in less than a decade, learning analytics is one of the fastest growing fields in educational inquiry (Slade & Prinsloo, 2013). However, “despite huge interests in analytics across various stakeholders—governments, educational institutions, teachers, and learners—learning analytics is still facing many challenges when it comes to larger adoption” (Joksimovic et al., 2019, p. 6137). Learning analytics uses cutting-edge analytical software to analyze large amounts of data to help identify trends and patterns for developing best practices in education and aiding data-driven decision-making. “Learning analytics refers to the application of analytic techniques to analyze educational data, which includes providing data about learner and teacher activities, identifying patterns of behavior and providing actionable information to improve learning and learning related activities” (Maseleno et al., 2018, p.1124).

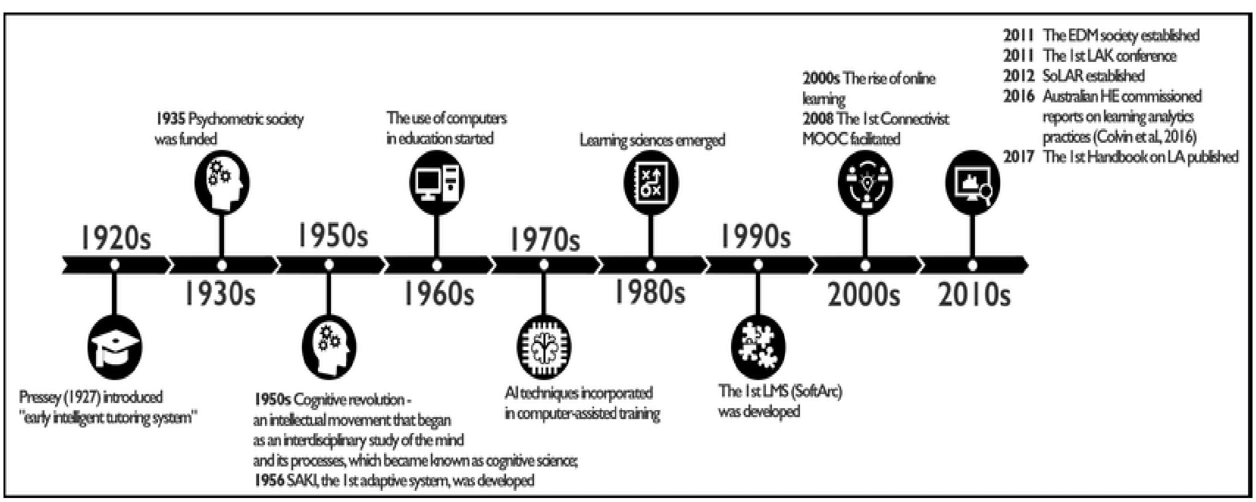
Seeing how learning analytics can significantly impact the future of education is easy; the problem lies in how to get there. While being a fairly new topic in education, learning analytics can trace its roots back to business intelligence and web analytics (Elias, 2011); consequently, much of the early scholarship concerning analytics deals with business applications. However, in 2010 the Society for Learning Analytics Research (SoLAR) initiated the first Learning Analytics and Knowledge Conference (1st International Conference on Learning Analytics and Knowledge, 2011). After this historical meeting, learning analytics was established as a major topic for stakeholders involved in the future of education. Over the past decade, several organizations and publications were founded to provide avenues for disseminating information and research concerning learning analytics. The emergence of learning analytics is grounded by a review of the historical context of learning analytics, types of tools available to implement learning analytics, and standards underlying the development of learning analytics.

Historical Context

Over the past 60 years, computers have helped to collect and process data. In the past, computers have been efficient at helping with the sorting of data into pre-established classifications and files. With more advanced computer systems, increasing amounts of data are collected which has led to the development of using computerized analytics to process the data (Cooper, 2012). Before analytics, data were fit into preset categories defined by the human operator. Learning analytics can identify new categories that can be used to group the massive amounts of data collected every second (Siemens, 2013). See Figure 1 for a graphic representation of the evolution of learning analytics.

Figure 1

Evolution of Learning Analytics (Joksimovic et al., 2019)



Several businesses are notable because of their early recognition of the power of using data to predict customer demand and preferences. These businesses have successfully used analytics to grow their companies, increase revenue, and improve customer satisfaction. Four companies that stand out as pioneers in the analytics arena, because of early adoption of analytic practices and their meteoric rise to success, are Amazon, Facebook, Google, and Apple (Miguel & Casado, 2016). While these four corporations inspired numerous imitators throughout the business world, educational institutions began to adapt already proven and successful analytics practices to improve education and drive curriculum (Davenport & Dyché, 2013). Each of the four companies used data and analytics to achieve success in different ways. By borrowing parts of each company's data-driven policy, educational institutions started tapping into the wealth of data available to improve education. For example, assume you are searching Amazon for a particular book. While making your decision, Amazon will use your search information and any personal information they have to send many additional suggestions for reading material. In a school setting, students who have a choice in selection of reading material might receive suggestions based on their personal characteristics as well as their current and prior searches. The four companies listed above, and numerous other companies as well, will send suggestions, nudges, and reminders. Educators can use similar approaches as simple as reminding students of due dates.

Businesses were the first sector to realize the potential of harnessing the vast amounts of data being collected to help inform decision-making. Businesses have primarily used analytics as a tool to optimize their profits. For example, by applying analytics to the massive amounts of data generated by an online shopping website, a company can better predict what consumers are going to want. Businesses are free to use these data because, by using the website, consumers are implicitly allowing data to be collected concerning their activities on the website. The company or website owns the data collected and can enhance their objectives by using the electronic information left behind by the visiting customer (Madrigal, 2012).

In a time of decreasing budgets and increasing expectations, education institutions are looking at how businesses have used data and analytics to increase profits and improve customer satisfaction (Henchsen, 2014). In less than a decade, many businesses successfully used analytics in their dizzying drives to success. Change in education happens incrementally and over what seems like incredibly slow amounts of time in comparison. By adopting the successful analytic practices that businesses have made commonplace, education institutions want similar quick successes. The recent frequency of the use of learning analytics when discussing best practices in education may lead one to believe that learning analytics is a relatively new method being used in educational pedagogy. This, however, is not the case. Educators have long been using data to help make decisions. With the advent of computers and the growing capability to look at larger and larger sets of data, learning analytics has evolved "as a key strategy intended to foster improvement in public schools and universities alike" (Coburn & Turner, 2012, p. 99).

Types of Tools

Because learning analytics is new territory on the educational landscape, much confusion exists over the role analytics should assume. People can agree that there is a surplus of data in the education arena to be utilized to help understand today's learner. However, when tasked with creating a plan, educators know learning analytics can be useful but are stymied by not knowing how to implement plans to make learning analytics reachable for everyone. Many educators know what learning analytics is, but being able to use data for analytics is beyond their reach (Cho & Wayman, 2014). According to Mandinach and Schildkamp (2020), "the focus should be continuously adapting instruction in the classroom and beyond, to facilitate and optimize students' learning processes, taking in to account learners' needs and individual characteristics" (Section 2.). Many products for implementing learning analytics, reflecting technology in general and/or use of big data in varied contexts and approaches, are available commercially (Hodges & Prater, 2014). Commercial uses include education vendors using analytics for education tools that adapt instruction to the user to create a better learning experience or implementing learning management systems that help schools, teachers, and students track an individual's progress (Hodges & Prater, 2014). Learning management systems help with registering, grading, and assessing students (Siemens, 2013). Numerous products are under development to be used in K-12 classrooms as teachers begin to adopt more and more strategies for teaching that embrace data.

Platforms. A platform is an integrated set of online learning tools that facilitate delivery and management of instruction. One area of research about learning analytics covers the behavior of users of different online learning platforms (Means et al., 2009). The days of having classrooms consisting solely of textbooks, papers, and pens are long gone. Today's learning environments range from 100% online to a hybrid of traditional learning and online learning. There are online classes that exist without an instructor, and even traditional classrooms disseminate instruction via online tools. With the proliferation of online tools available to students and instructors, determining what platform or type of platform works best to facilitate learning is challenging (Means et al., 2009; Swan, 2005). To meet the needs of institutions, educators and students are seeking online platforms to assist or substitute for traditional instruction. Studies of the efficacy of various platforms and programs range from the qualitative to the quantitative and track data dealing with ease of use, how often users interface with the data, and eventual levels of student success (Means et al., 2009).

Dashboards. A dashboard is the first screen a user encounters when logging in or initiating action with an online learning platform or learning management system. Learning analytics relies on data. Various ways exist to collect data that analysts can use, but a growing trend is to use the data collected by online learning platforms and learning management systems. Considerable scholarship deals directly with the success and user-friendliness of dashboards (Klerkx et al., 2017; Verbert et al., 2013). Often, user success can be predicted on ease of navigation and intensiveness of the experience. Dashboards collect personal information to make predictions about future actions of the user (Verbert et al., 2013).

Assessments. One of the main roles of educators is to assess their students' acquisition and mastery of skills and knowledge. While most teachers become adept at informally conducting assessments, both formative and summative, standardized results are useful. Standardized tests have been one of the main tools to determine students' success. Use of standardized tests to collect data goes back decades for every academic institution in the country. Using learning analytics to analyze these data is of primary interest in educational inquiry. Learning analytics has the potential to view the bigger picture and identify trends and patterns previously unseen (Clow, 2012; Serrano-Laguna et al., 2012). On a smaller scale, online learning platforms and other electronic education programs can analyze individual user data to help determine whether a learner is reaching mastery of a topic or still needs assistance. By being able to predict in real time what a student needs to succeed could be the push needed by a learner to achieve success. Being able to understand why students do what they do has long been an interest of educators. Learning analytics can use data generated from a variety of assessments to make headway in understanding students' actions and predicting future actions based on past actions (Cech et al., 2018; McBrien et al., 2009; Means et al., 2009).

Real-World Experiences. As education moves into the future, providing learning experiences that mimic reality has become relevant (McBrien et al., 2009). Placing students who are in the process of mastering skills into potentially dangerous, real-world situations is an unsound educational practice. With augmented reality and virtual environments, creating worlds that are modeled on reality, but where the student can still be kept safe, is possible. The line between gaming and education environments is becoming fainter. There is an obvious push in learning analytics scholarship to discover ways in which gaming can create rich and multivariate environments to help students achieve greater success (Marone, 2016; Means et al., 2009; Serranao-Laguna et al., 2012). In order to be successful, the virtual environment has to be as close to reality as possible. Software systems have to be sophisticated enough to react as quickly and accurately as a real situation. Real-time analytics makes timely reaction possible.

MOOCs. Over the past decade, more and more schools and organizations are offering Massive Online Open Courses (MOOCs). The reasoning behind creating and offering MOOCs is clear. Technology allows individuals and institutions to spread knowledge far beyond their brick and mortar boundaries to populations that may have previously been denied access. Some of the most well-known universities are offering courses, created by well-known scholars, to people who traditionally would not have had access. MOOCs provide ideal conditions to be studied using learning analytics. MOOCs have large student populations, and all activity happens online via online learning platforms; they generate more than enough data to be used for applications of learning analytics. While MOOCs show much potential with their large enrollments, their main problem is their very large dropout rates (Means et al., 2009; Nawrot & Doucet, 2014).

Drop-out Monitoring. Being able to predict students who may be vulnerable to dropping out of a school or a program, and why, is of great interest in educational inquiry (Cech et al., 2015; Nawrot & Doucet, 2014). An abundance of scholarship is dedicated to looking at attrition and underlying reasons as well as ways to predict who is in danger of dropping out. By looking at past data, making predictions about students who are susceptible to dropping out is possible (Siemens, 2013). Monitoring students' participation in learning- management systems may provide education institutions forewarning of a student's likelihood to drop out. Struggling students can be more easily identified before they drop out as opposed to after they drop out. Not only can monitoring a student's activity on a learning management system give education institutions information about academic problems, but also a growing contingent believes that being made aware of any possible psychological or social issue is of paramount importance (Siemens, 2013).

Purdue University is certainly not the only institution using analytics; however, Purdue provides a well-known, documented example of using analytics for early intervention (Arnold, 2010; Arnold & Pistilli, 2012; Campbell et al., 2007; Fritz, 2011). Purdue's program Course Signals is used to analyze data in real time to quickly identify students at risk (Arnold & Pistilli, 2012). The developers of Course Signals wanted to tap into the potential of using the massive amounts of data that a school collects through various programs. Variables used by the algorithm include students' demographics, course loads, relative performance compared to other students, and activity level. Information is pulled from Blackboard, Purdue's learning management system, and other online sources (Arnold & Pistilli, 2012). Course Signals has shown improvement in student grades since implementation in 2007.

Underlying Standards

Privacy. A legal issue concerning learning analytics is privacy. Not so long ago, individuals controlled who accessed their information. People kept paper files, paper diaries, paper copies of bills and receipts, and paper copies of correspondence with a level of confidence that their records would remain private. Today, people are increasingly living their lives online or paperless. Individual information still exists, but no longer in possession of the individual (Solove, 2011). The fourth amendment of the United States Constitution says:

> The right of the people to be secure in their persons, houses, papers, and effects, against unreasonable searches and seizures, shall not be violated, and no Warrants shall issue, but upon probable cause, supported by Oath or affirmation, and particularly describing the place to be searched, and the persons or things to be seized (U.S. Constitution, 1791).

Before the technological era, individuals and their information were protected. More recently, the Supreme Court has interpreted the fourth amendment in a way that allows for the "third party doctrine," giving access to what used to be considered private information if it is in the hands of a third party (Solove, 2011). An example of a third party would be a company providing online storage for school or student files and documents. If the files and documents stored in the online storage are not protected and private, several possible problems could emerge. One such problem occurs over the ownership of any intellectual property. Another problem concerns students' grades and health records and who would be able to access that information.

Another important law concerning privacy and education is the Family Education Rights and Privacy Act (FERPA). FERPA ensures the privacy of all education records of minors and adults who attend an institution receiving federal monies. Schools are prohibited from sharing data about a student with third parties unless students or their guardians have permitted the school to do so (Family Education Rights and Privacy Act, 1974). In 2008, FERPA was extended to allow third parties who are under school supervision to have access to data. Third parties include volunteers, consultants, and other entities working for a school or district. For example, Google provides many districts and institutions with an array of applications including email, word processing, and cloud storage. Google collects data on how these applications are used and then uses the information for profit (Henchsen, 2014). Politically, the biggest question looming for public education concerning learning analytics is who owns the data and the output from the analysis of the data.

For years, education institutions have been collecting data but, for fear of violating federal privacy laws and the desire to protect students, data have been underutilized (Beaver & Weinbaum, 2015). The potential for understanding learners in new ways is pushing educators and researchers toward developing new systems for using learning analytics. While the possibilities are exciting, following enacted legislation is necessary. Systems need to be developed to ensure privacy and to protect individuals.

Social Justice. Social justice in education broadly deals with ensuring that all students are treated equally and have equal access to educational resources regardless of socioeconomic or other social factors. Often, violations of social justice are easy to identify while in other cases violations can go unnoticed. Seeing a much broader and more richly detailed landscape of education today is possible when using learning analytics (Slade & Prinsloo, 2013). Learning analytics has the potential to show where populations of students are being overlooked that otherwise may have gone unnoticed. Often, teachers and administrators are limited in what they see in their immediate environments. Learning analytics can take data from across the country to help practitioners in their search for equitable practices and techniques (Slade & Prinsloo, 2013).

Technology Advances. Artificial intelligence is a growing field permeating all aspects of society. Adaptive devices have entered homes, work places, and, soon, schools. The way the human brain works has proven to be hard to mimic. One way that scientists and engineers are going about creating artificial intelligence that can learn and adapt to new data, the way humans do, is by taking a constructivist approach. Engineers in adaptive robotics research are using constructivist models to help create artificial brains that mimic more closely the thought patterns and structures of the human brain. Working from Piaget's models of knowledge acquisition for children, artificial intelligence engineers are able to replicate, for robotic brains, human-like assimilation and accommodation of new data (Ziemke, 2001).

Infrastructure. While there is an excess of data on education and learning, much cannot be used because the collection methods are unclear. In order for data to produce valid and generalizable results, guidelines must be in place that dictate how the data are collected. Multiple institutions can be trying to answer similar questions with similar data, but the data cannot be compared unless the data have been collected in the same way. To use learning analytics to its full potential, data sources must be identified, methods for data storage must be developed, and strategies must be developed to facilitate interpretation. Areas of concern include deciding who has access to the data, who is permitted to manipulate the data, and how long an institution should keep the data (Murray, 2014). Methods for removing identifying factors also need to be determined and are dependent upon how the data and learning analytics are to be used (Beaver & Weinbaum, 2015). Clear protocols for all aspects of obtaining, storing, and using data for use in K-12 classrooms must be determined to create an ethical and clear process for using data to enhance instruction.

Research Literature

While learning analytics is “a major component of how education is being imagined and enacted” (Selwyn, 2019, p. 11), the adoption of learning analytics is slow to be implemented across all areas of education but especially in the K-12 classroom (Pierce & Cleary, 2016). Shattuck (2010) made the following generalization about teacher adoption of educational technology.

> It is generally agreed upon by most educational technology researchers that the integration of technology promised in the 1990s by the proponents of technology in education has not materialized despite the fact that billions of dollars have been spent on technology in schools…. To understand why technology integration has not succeeded, one must understand how … educational leadership practices impact how teachers perceive the use of technology within their classroom practices. (p.1)

Ross (2015) further explored use of technology through study of funding in schools and concluded, through analysis of school spending audits, that investment in technology is often wasted. More recently, Joksimovic et al. (2019) commented that “despite the popularity of learning analytics, increasing availability of data and learning analytics tools as well as ongoing noted importance of learning analytics in education there remains significant barriers and challenges in organizational adoption” (p. 53).

Current interest in learning analytics is evident from the many scholars who are actively thinking about how to use learning analytics to improve learning. For many years, researchers writing about learning analytics had to rely on a small pool of peer-reviewed, published works in the field of education or from other fields using analytics. Currently, the quantity of research articles on the specific area of implementing learning analytics continues to expand. Most research articles suggest that serious work needs to occur in the field of learning analytics to ensure that learning analytics is used effectively and appropriately to help data-driven decision-making in education (Dawson, et al., 2019; Selwyn, 2019). On a positive note, Dawson, et al. (2019) commented that “while LA research has not yet reached its potential, it is advancing and is on the right path to fulfill its stated promise of generating sector wide transformations” (p. 454).

The following paragraphs cover research literature from areas of greatest relevance for understanding the role of the K-12 classroom teacher in embracing learning analytics. Factors underlying the adoption of learning analytics include data skills, training needs, and leadership roles. Also relevant are frameworks for learning design that will enhance the benefits of learning analytics—consideration of characteristics of learners, status of the infrastructure underlying adoption of learning analytics, and use of data for personalizing instruction. Last, several empirical studies of educator awareness, usage, resources, and attitudes in regard to use of learning analytics reveal the voices of K-12 teachers.

Factors Underlying Adoption of Learning Analytics

Data Skill Competency. For many educators, learning analytics is still intimidating, and finding practitioners untrained in statistics who use learning analytics regularly is seemingly rare (Michos et al., 2020). A major weakness of scholarship on learning analytics is the lack of information on applications within the comfort zones of most education practitioners. Learning analytics still seems like an elite discipline only for the initiated. While there is a plethora of literature looking at what learning analytics is and how to use it, the literature seems to ignore how a typical, education practitioner can incorporate learning analytics into daily practices (Cho & Wayman, 2014). The skill set needed by tomorrow’s teachers will more closely resemble those of data analysts and facilitators. An understanding of such basic statistics as measures of central tendency, variance, measurement error, and confidence intervals will likely become more evident in teacher training. With data running the show, the role of a teacher will have to evolve (Ferguson, 2012). Schools will need to be redesigned to incorporate new technologies and new methods of acquiring knowledge (Bienkowski et al., 2012).

The scholarship addresses uses of learning analytics but fails to make the case about how easily accessible or even understandable the methodologies can be for those who are untrained in analytic practices. The language still being used in analytics relies heavily on that used by traditional statisticians. The difficulty understanding or even accessing the scholarship involving learning analytics makes many avoid incorporating it into personal pedagogy. "Without an infrastructure that can provide teachers and school leaders data they understand and use, the potential for data will not be realized" (Murray, 2014, p.5).

The move towards a learning environment that is controlled by data will not be easy. There are many, both in the world of education and out, who consider the word 'data,' a four-letter word (Zavadsky & Dolejs, 2006). Data are associated with testing; students, teachers, and parents often consider testing to be torturous. Testing delivers a score that is supposed to represent a student's acquisition of knowledge or mastery of a learning target. Each student's score can be compared to the scores of other students across the district, state, or country. Testing scores might or might not recognize where a student's baseline was before the unit of instruction or take into consideration how a student learns and demonstrates that learning (Beaver & Weinbaum, 2015). So much data are collected about students on a daily basis, from the minute they enter the education system, that finding valid uses for the data seems logical.

> …simply having a wealth of data sitting in a computer somewhere does not improve a school—it takes human capital to interpret the data and to use it to guide and implement meaningful reforms that improve the delivery of high-quality instruction. (Beaver & Weinbaum, 2015, p. 479)

Education's primary difference from business is the element of human capital. For many people, data conjure feelings of dread. Students think of data like test scores, parents think of data as a judgment of their child's success, and teachers think of data as a means by which to gauge their effectiveness. For analytics to be successful in education, stakeholders have to be on board and be aware of the potential data can have as an instrument to improve instruction and the learning environment. People need to be reintroduced to data as a tool instead of an instrument for punishment. Using analytics does not mean removing teachers and other humans from the learning process with a universal reliance on computer-generated data. Cech et al. (2018) have commented that “analytics cannot replace educators” (p. 153). Instead, analytics can be used to remove the guesswork from curriculum planning at the individual, classroom, and institutional levels.

Learning analytics needs to be accessible and understandable by all levels of educators regardless of technical training. The bottom line is that educators can benefit from access to the information that analytics supplies while not necessarily knowing the mechanics of how the results are generated. Being able to use the output from learning analytics does not require a technological background (Siemens & Long, 2011). Educators have suggested how to implement programs using learning analytics and how to familiarize members of the education community with learning analytics with little success. Most participants still hear learning analytics and think data and numbers. If educators can move past the quantitative aspect of analytics and begin understanding and interpreting the data qualitatively, learning analytics can help all members of the education community with data-driven decision-making (Siemens & Long, 2011). To provide data to educators in a user-friendly form is necessary for improving curriculum development and classroom instruction (Murray, 2014).

Training Needs. Using analytics to restructure education will not remove the humanity from schooling. Instead, using analytics in education will enable the teacher to increase the quality of human interaction with students. Instead of spending time to create universal lesson plans to accommodate students who are different types of learners, interested in different topics, and possess various levels of prior knowledge, teachers can spend time becoming experts in their fields and use this expertise to help students gain an insight at levels previously not possible. However, educators must be trained to use the special tools of learning analytics (Murray, 2014). The Alliance for Excellent Education report, *Capacity Enablers and Barriers for Learning Analytics: Implications for Policy and Practice* (Wolf et al., 2014, p. 5), identified four key areas, three of which emphasize training, as a focus for implementing learning analytics programs:

- providing infrastructure and technology that fosters transparency between educators, administrators, parents, and students;
- shifting to a culture of data-informed decision making by well-trained educators;
- strengthening human capital at all levels of the education system—states, districts, schools, and classrooms—by training educators and administrators to use and understand data; and
- supporting teachers through professional learning communities, including data teams, intra-district communication, and social media.

By integrating analytics systems with learning design, teachers will have more time to foster learning and support students. If individualizing instruction for all students is every teacher's goal, tailoring curriculum to meet the needs of each student is an impossible task when left to the teacher alone. A data-driven curriculum will use data from a myriad of sources to individualize instruction for each and every student. As soon as a student shows mastery of a learning target, the curriculum can move the student on to the next target, allowing extra time to spend on concepts the student has a harder time mastering. Aldunate and Nussbaum (2013) found that "teachers who are early technology adopters and commit a significant portion of their time to incorporating educational technology into their teaching are more likely to adopt new technology, regardless of its complexity" (p. 519).

Last, but most certainly not least, is the goal to enable all stakeholders to get proper training on how to use and interpret data. Students benefit from acquiring self-monitoring skills about when and how to ask for help (Wang, 2016). Teachers benefit from using data to tweak curriculum to ensure mastery of learning objectives (Aldunate & Nussbaum, 2013). Administrators benefit from knowing how to use analytics to make policy (Mandinach & Gummer, 2013). Michos et al. (2020) continue to stress the common theme that "substantial professional development of the teaching workforce around technology, data, its processing and uses" (p.98) is imperative.

Leadership. In a discussion of critical issues facing school leaders as they implement use of data for informed decision-making, Murray (2014) concluded the following:

> I truly hope that data-informed decision-making will not have the same fate as so many other failed educational reform movements…. School leaders must take the time to clarify the role of data in the school improvement process, must go beyond student

> achievement data to use multiple types of data, must develop ways to organize and present data in a user-friendly format, and must provide ongoing, targeted professional support to help educators develop the knowledge and skills to effectively analyze and use data to improve schools and student learning. (p. 6)

In general, school administrators at all levels within school districts must assume leadership roles if their schools are to succeed. In applications of learning analytics, often the school principal plays the starring role (Cho & Wayman, 2014; Sun et al., 2016). "Policymakers should invest in skill building for data analysis for school and district personnel so that they might be better equipped to respond to the demands of accountability policies" (Beaver & Weinbaum, 2015, p.483). Cho and Wayman, (2014) "emphasize that it is the unique duty of school and district leaders to share their visions regarding data use, as well as to engage in dialogue with their communities about the natures of schooling and data use" (p. 1).

Barriers to greater use of learning analytics in K-12 schools are significantly affected by funding priorities. Many options for using learning analytics are easily obtained but each school funding body must make a commitment to developing the infrastructure needed for success. According to Pierce and Cleary (2016),

> Historically implementing, maintaining and managing educational technology has been difficult in K-12 educational systems…. A major public policy question is how to best insure educational technology resources reach all K-12 students in the shortest and most equitable way possible. …efforts to implement educational technology in K-12 systems must overcome challenges and risks. (p.863)

Pierce and Cleary (2016) describe in detail how infrastructure and delivery of services along with implementation and integration of services affect the overall commitment to educational change and comment that teachers must have opportunities for ready access and mastery of educational applications of technology for their classes.

Herold (2016) has concluded that school officials often embrace technology that enables them to comply with requirements but seldom go beyond the basics. Much debate exists in school systems and grandiose visions emerge but then too many barriers—privacy, cost, training, interest, time—slow the momentum. With such impasse, grants that provide personnel, training, and resource can sometimes provide the needed impetus; but, again, someone has to take the initiative and make the time to apply for grants. Cech et al. (2018) point out that "educators are often overloaded and time is precious" (p.152). Pierce and Cleary (2016) mention that seeking funds is a never-ending process for K-12 systems and that Federal, State, and private sector agencies are key partners in the implementation of new technologies. According to Arnold et al. (2014), "assuming all institutions have the same probability of success … is a costly mistake. …LA projects require a signification investment, and …should not be undertaken without thoughtful and deliberate consideration …." (p. 163).

Frameworks for Learning Design

Skills needed to navigate the world today are different from the skills needed in the past (Cotton et al., 2010)). No chance exists for society regressing back to an earlier point. Society can only move forward and must embrace the changes technology has created. There is no time to lament a loss of literacy; it is time to begin understanding how analytics are part of a new literacy and to develop strategies in education to best incorporate these changes into a new organization. The traditional school filled with individual classrooms and a hierarchal organization of personnel and grade levels is no longer a workable model for an education institution. Instead, now is the time to embrace individualized plans for knowledge acquisition and mastery. New ways of using and analyzing data for individuals and larger populations allow students to use personal data to set benchmarks and learning targets (Brown, 2011). The use of big data in education is going to allow educators to look at how learning happens and create applications that will best serve different learners by moving past differentiated education into individualized education (Beaver & Weinbaum, 2015; Coburn & Turner, 2012).

Learning analytics and learning design provide a synergy of strategies to enable instruction to be individualized and modified to meet the specific needs of each student. While learning analytics provides data about student characteristics, learning design provides the framework for selecting strategies to reach desired learning outcomes (Ifenthaler, 2017a). Instructional design has long provided models for the development of objectives, activities, and assessments to meet educational goals of specific populations of students. Now that analytics have developed to provide individual data to be used in real-time, learning design that incorporates learning analytics will facilitate interventions and direction for individualized instruction. Digital learning environments aim "to improve the student's experience" and promote "deeper engagement to achieve higher order competencies and learning outcomes as well as guarantee high-quality learning design and instruction" (Ifenthaler, 2017b, p. 401). In learning design, once student characteristics are identified, first the learning objectives are defined and then the technology to enable the activities for acquisition are selected—not the other way where the technology is first chosen and the objectives are manipulated to fit.

The challenge in learning design for K-12 classrooms is the alignment of the more traditional instructional design model with the use of analytics. Schmitz et al. (2017) have aptly described the process of integration.

> A teacher or educational designer works on all phases of an instruction: starting from the definition of prior knowledge prerequisites of the target student group, the learning objectives and outcomes, and the design of assessments to test if the outcomes have been achieved…. The teaching activities and resources are provided increasingly over IT infrastructures…. This offers the possibility to use LA as part of the learning environment and the LD. (p.8)

A number of authors have recommended strategies related to learning design that will enhance the instructional process. (Cech, et al., 2018; Drachsler & Greller, 2012; Fitzgerald et al., 2018; Pierce & Cleary, 2016).

Characteristics of Learners. Student characteristics are available, through learning analytics, to be used in planning instructional programs across varied populations. Cech, et al. (2015) have identified student characteristics differentiated by two categories—retention factors that are "difficult to influence, but have predictive capabilities," and "those which are predictive and have the potential to be influenced" (p.3). Factors from the first category, difficult to influence, include socioeconomic status, family size and structure, parent characteristics, educational attitudes, and academic performance. An example of an effect for the characteristic of academic performance relates to prior, low grade-point average as a precursor to doing poorly in secondary education. Factors from the second category, potential to be influenced, include social engagement, academic performance, and school performance. An example of an effect for the characteristic of social engagement relates to effects from participation in extracurricular activities.

While the approach of Cech et al. (2018) is more macro than micro in applying analytics, K-12 teachers who are following a model of learning design will find specific learner characteristics, both related to background and academic factors, useful in assessing the characteristics of their students as they formulate objectives and develop learning activities. The Cech et al. (2018) analysis is literature based and provides specific factors and sub-factors with descriptions of overall effects. Comparisons are presented to illustrate how the maturity of the data model eventually goes through several stages of data competency: ad hoc followed by defined, integrated, optimized, and advanced. K-12 teachers will likely benefit from the availability of data (defined stage) and subsequent use of the data in classroom applications (integrated stage).

Infrastructure. Pierce and Cleary (2016) propose a model of instructional design where the infrastructure and delivery of service is first assessed, followed by implementation and integrations of services, and finally assessment and adjustment. The first phase includes systems and platforms, application management, networks, and personal computing devices. The second phase includes applications and device procurement, student educational technology applications with teacher training, and curriculum development. The third phase includes evaluation and feedback. Since the model includes a specific phase focusing on infrastructure, the model could be useful to teachers, who would be involved in phase two, to ascertain what types of resources are available for the design of learning. Pierce and Cleary (2016) stress that "implementation of any type of educational technologies in K-12 schools cannot be done effectively unless teachers can readily access and master the educational applications used in their classes" (p. 871).

Personalization. Personalization of learning was proposed by Fitzgerald et al. (2018) as an important factor to consider in technology-enhanced learning. Personalization of learning is based on a shift from the one size fits all system to an environment that gives control to learners (Chatti & Muslim, 2019). As teachers consider ways to design instruction, Fitzgerald et al.

(2018) suggest a methodology that covers content, assessment, teaching and learning strategies plus learner and teacher choices as well as personal characteristics of the learner. Chatti and Muslim (2019) recognize that learning analytics is opening up new avenues for personalization by showing that embracing learner characteristics helps students achieve their own goals and needs. Learning analytics "focuses on the development of methods for analyzing and detecting patterns … and leverages those methods to support the learning experience" (p.247).

Teacher involvement in the development of learning design is critical for making the use of learning analytics relevant to the classroom. "The presentation of educational data to teachers or students requires meaningful sense making to effectively support data-driven actions" (Michos et al., 2020, p. 94). Combining learning analytics and learning design results in production of educational objectives and pedagogy that involve reflection, decision-making, and eventual improvement of learning (Mangaroska & Giannakos, 2018).

Empirical Studies of K-12 Education

In regard to teachers and their reactions, finding out how those on the front lines of innovation react to the possibilities of embracing learning analytics will contribute to the determination of how much and what types of data gathering are useful in the future. The use of learning analytics shows great promise for K-12 education with lots of hype but an overview of reality will provide some guidance to those who are strong advocates. Confirmation of the value of learning analytics in comparison to the high hope of the innovative learning technology is a critical component for advocating or not. Michos et al., (2020) concluded in their review of literature that few examples are available to document the involvement of K-12 teachers in design of instruction using learning analytics. Dellinger (2019) made similar mention of the lack of empirical studies documenting the value of learning analytics in the K-12 classroom and commented that considerably more research has been conducted in higher education.

Research studies about use of learning analytics in the area of K-12 education can be categorized in four areas of a broadly interpreted definition of survey methodology: questionnaires, interviews, case studies, and literature reviews. Some of the literature does include the opinions of teachers but often the results reflect administrative personnel at the local and district levels and even universities. Best and Kahn (1998) state the following in regard to survey research:

> In analyzing political, social, or economic conditions, one of the first steps is to get … a picture of conditions that prevail or that are developing. These data may be … inferred from a study of a sample group carefully selected from the total population…. The survey is an important type of study. It must not be confused with the more clerical routine of gathering and tabulating figures. It involves a clearly defined problem and definite objectives. (p. 116).

Questionnaires. Questionnaire data across three studies, conducted outside the United States, generally found an interest in embracing technology but anxiety about attempting to do so. Drachsler and Greller (2012) reported results from 156 responses to a survey about confidence in learning analytics among practitioners and researchers from 31 countries. Although the researchers promoted the questionnaire equally to schools, universities, and other education sectors, K-12 teachers represented 9% while higher education represented 74% of the respondents. Results concerning confidence in learning analytics revealed “substantial uncertainties and relatively low confidence levels, paired with high expectations and wishful thinking” (p. 1). A short survey about use of technology was given to 100 teachers in Chile

(Aldunate & Nussbaum, 2013) where results showed that experience with technology in general was the primary factor in adopting new technologies in the classroom. Therefore, due to varied experiences with technology, there were substantial differences in adoption attitudes. A later questionnaire concerning adoption of electronic textbooks in a Hong Kong school (Chiu, 2016) found from 306 responses of secondary teachers that "anxiety and positive attitude were the main innovation" (p. 2).

Interviews. Two examples of an interview methodology related to data use in K-12 environments emerged from the literature review search. The two studies are differentiated by macro versus micro focus. Findings in the school-wide applications seemed more consistent whereas the classroom usage seemed less understood. Beaver and Weinbaum (2015) visited 11 elementary and secondary schools in Pennsylvania to conduct 97 interviews of school administrators and teachers concerning use of state measures of performance-based accountability. Findings indicated that school personnel use state data to improve their schools while fundamentally questioning the validity of the data. Teachers indicated that state test results indirectly affect goals via directives from administration. State test data were used by 70% of the schools to provide remediation. Dellinger (2019), who conducted hour-long, semi-structured interviews with 14 public school administrators in a regional setting in Texas, focused on the decision-making process for adoption of learning analytics. In general, Dellinger concluded that understanding of learning analytics varies across administrators, that knowledge of what data are available is unclear, and that opportunities and challenges persist. Dellinger concluded that more research is needed with a greater breath of stakeholders including teachers.

Case Studies. Two examples of case studies related to learning analytics in K-12 settings emerged from the literature review. Based on a variety of methods and cultures, findings were somewhat varied but both did focus on the involvement of teachers in assessing priorities and in having the training needed to make appropriate decisions for use.

Cho and Wayman (2014) used interview, focus groups, and observation to study practices of data use by teachers and administrators in three school districts in Texas. Data collection consisted of semi-structured interviews of 17 central office administrators, focus groups of four to six participants totaling 46 teachers and 19 school administrators, and 13 observation sessions in the field of 60 to 90 minutes. Results indicated the following:

> Although computer data systems can support changes to practice, we found that agency for change rested in people, not in the technologies themselves. Indeed, teachers' sensemaking about "data" and "data use" shaped whether and how systems were used in practice. Although central offices could be important to sensemaking, this role was often underplayed. …recommendations include recognizing implementation as an extended period of social adjustment. Further, we emphasize that it is the unique duty of school and district leaders to share their visions regarding data use, as well as to engage in dialogue with their communities about the natures of schooling and data use. (Cho & Wayman, 2014, p. 2-3)

Michos et al. (2020) assessed teacher experiences in incorporating learning analytic strategies in their instruction. The study lasted approximately two years and included 33 teachers from a high school in Catalonia, Spain and 30 teachers from primary and secondary schools in New York City. The researchers used a five-stage analysis including analyzing current practices, documenting current practices, training on learning design, classroom enactment, and collaborative reflection. Findings emphasized training in the context of "learning about data and the methods of data analysis, but also involving them in the creative-side of how analytics are designed and developed" (p. 98). The authors developed five principles for involving teachers in learning analytics design: identify teacher problems encountered with learning analytics, connect the problems with learning analytics options, teacher collaboration, provide time for development, and consider ethical issues relating to students.

Literature Reviews. Three articles based their conclusions and recommendations on a review of literature as a data collection strategy. Of course, none of these gathered opinions about learning analytics from individuals, but they do provide relevant findings for implementation. Furthermore, they are recent publications and show that considerable literature is available in various formats to guide the implementation by teachers of learning analytics in K-12 education. Two of the articles used the concept of personalization of learning in their titles (Fitzgerald et al., 2018; Roberts-Mahoney et al., 2016) and a third article covered learner characteristics (Cech et al., 2018) that could enhance use of learning design.

Roberts-Mahoney et al. (2016) analyzed 12 documents, deemed significant policy papers, by coding them in regard to four primary points of emphasis. They concluded with the following statement:

> The core issue is not how new digital technology should be used to transform education…, but how can our educational institutions and practices be supported and transformed in order to effectively mobilize technology and generate technological literacies in line with progressive, democratic, and sustainable communities and futures. (p. 418)

Fitzgerald et al. (2018) reviewed what they termed to be six "case studies" in regard to personalization of learning. The examples studied included tutoring, adaptive assessment, science inquiry, gaming, learning analytics, and personalized books. The result included design guidelines for personalizing instruction using technology. They recommend that teachers be asked to consider how to provide personal support for their students in their online activities.

Cech et al. (2018) used literature-based recommendations for ways to enhance learning through analysis of student characteristics—those that reflect academic performance data and those that reflect student demographics. By such consideration of characteristics, in a sense, they are implying personalization of learning. They conclude their analysis and development of a model for use of data in secondary education with the recommendation that "as technology continues to develop, we must intentionally develop policies and practice to leverage data as a valuable resource for student success. Our data are becoming a valuable and deep resource to improve the lives of students and educators" (p. 154).

Conceptual Framework

The basis for the survey of teacher opinions of awareness, usage, resources, and attitudes in regard to implementing learning analytics in K-12 classrooms can be conceptualized within two frameworks. The first framework relates to evidenced-based decision making; the second framework relates to a model proposed by Drachsler and Greller (2012) for "encapsulating the design requirements for the practical application of learning analytics" (p. 1). While the two approaches to defining a conceptual framework for the current study are quite different in focus, both approaches have evolved from the literature review and provide a rationale for how data were obtained, analyzed, and interpreted.

Evidenced-Based Decision Making Framework

A growing trend across many disciplines is use of data as a basis for decision-making. While intuition has some merit in making decisions, the "gut" instinct, in regard to evidenced decision-making must eventually be verified with concrete evidence. The philosophy of positivism (Oxford, 2020), where "every rationally justifiable assertion can be scientifically verified or is capable of logical or mathematical proof, and that therefore rejects metaphysics and theism, underlies the validity of evidence-based decision making." Scientific verification can range from comprehensive long-term and wide-spread collection of data to smaller, localized investigations. The more comprehensive studies often result in greater generalizability and contribute to theoretical development. The latter studies are often referred to as exploratory research, a research strategy where the goal is to provide insight in to a situation of significance.

Sun et al. (2016) provided a comprehensive review of data-driven school leadership and identified 60 studies related to the topic and published within a 10-year span. One section of the review covered development of decision-making capacity by teachers.

> Studies we consulted suggested that teachers were pressed by incompatible and multiple initiatives to use student data while lacking training in how to use data in their own context…. Professional development helped teachers to interpret and analyze various forms of data and use them to set goals for students, to monitor standards, to implement evidence- or research-based effective instructional strategies, and to develop new instructional strategies that worked…. Such support could motivate teachers to be more committed to data use and to alter their teaching practices to enhance learning of each of their students. (pp. 97-98)

Based on a session from the 2018 American Educational Research Association Conference, participants concluded that "policymakers have stressed the need for education to become an evidence-based field, causing educators to rely more on data and research evidence, and not just on experience and intuition" (Mandinach & Schildkamp, 2020, para. 1).

Learning Analytics Framework

For use in guiding studies of applications of learning analytics, Drachsler and Greller (2012) developed a learning analytics framework that consists of six dimensions:

- Stakeholders: the contributors and beneficiaries of learning analytics.
- Objectives: set goals that one wants to achieve.
- Data: the educational datasets and their environment in which they occur and are shared.
- Method: technologies, algorithms, and theories that carry the analysis.
- Constraints: restrictions or potential limitations for anticipated benefits.
- Competence: user requirements to exploit benefits. (p. 1)

The four areas of the current study—awareness, usage, resources, and attitudes that are highlighted by the research questions—were inspired by the six dimensions of the framework (Drachsler & Greller, 2012) .

- Stakeholders: *teachers*, a major stakeholder in use of learning analytics, were surveyed.
- Objectives: *awareness* of a concept is integral to setting learning objectives.
- Data and Method: *usage* of a concept depends on access to data and method.
- Competence: *resources* enhance competence.
- Constraints: positive *attitudes* reduce potential constraints.

The six dimensions of the learning analytics framework were intended to "inform and support learners, teachers, and their institutions in better understanding and predicting learning needs and performance" (Greller & Drachsler, 2012, p. 42). The dimensions were explored to "act as a useful guide for setting up Learning Analytics service in support of … quality assurance, curriculum development, and in improving teacher effectiveness and efficiency" (Greller & Drachsler, 2012, p. 42).

Summary

In general, the literature on learning analytics is positive about the potential of using big data to facilitate classroom instruction at all levels of education but is somewhat negative about the logistics for implementation. The classic literature provides a broad overview of how learning technologies have evolved and laid the foundation for current methodologies in use of big data to improve classroom instruction. In addition, proven methods from the business sector, used to influence customer satisfaction and increase profits, provide a second impetus for developing data-driven instructional strategies. The research literature on learning analytics is broad but lacks a cohesive approach for further study. Many publications describe benefits of learning analytics and rationales for implementation in such areas as leadership, training, learner characteristics, and design of instruction. However, more empirical study, both qualitative and quantitative, is needed to document the efforts of teachers in the K-12 classroom as they begin to see the benefits of using data to guide instruction. A strong conceptual framework, including stakeholder and infrastructure effects, is evolving for use in data-driven studies of learning analytics.

Chapter 3: Methodology

The focus of this investigation was to examine the validity of the predictions made by the Horizon 2013 and 2014 Reports (Johnson et al., 2013; Johnson et al., 2014) concerning the imminent implementation of learning analytics in K-12 settings. Innovation in public schools is typically dependent on funding, whether from local and state funds or from grants. Use of learning analytics in instruction brings with it the need for an additional funding source, not only for instructional materials but also for training of teachers and support staff and resources for instructional technology. Since funding issues in public schools start with state support and are further supported by local sources, investigation at the state level makes sense. The research setting for the current study focused on public schools across North Carolina. Gaining insight through self-report by teachers, the individuals identified by the Horizon Report as a major stakeholder in use of learning analytics, guided the methodology for use in validating the Horizon predictions.

Chapter 3 begins with an overview of the methodological approach of the study with reviews of the research questions, the design rationale, the role of the researcher, and ethical issues. Second, coverage of the participants, includes not only their description, but also, the effect of the 2020 pandemic on their selection. Third, review of the instrument protocols include the data source, IRB procedure, and data collection process. Fourth, treatment of data is described through the data coding and data analysis procedures. Finally, the issue of the trustworthiness of the findings is addressed.

Methodological Approach

Research Questions

The focus of the current study embodies the opinions of North Carolina teachers and their current level of engagement with learning analytics in the K-12 classroom. As provided in Chapter 1, the following four research questions focused on an investigation of the status of teachers' awareness, usage, resources, and attitude in regard to learning analytics.

1. Across total respondents and within selected subgroups of respondents, what is the level of *awareness* by K-12 teachers of learning analytics as a viable strategy to improve instruction?
2. Across total respondents and within selected subgroups of respondents, how have K-12 teachers shown *usage* of learning analytics themselves or observed others using learning analytics as a viable teaching strategy to improve instruction?
3. Across total respondents and within selected subgroups of respondents, what types of *resources* have been available to K-12 teachers for gaining skill in using learning analytics as a viable strategy to improve instruction?
4. Across total respondents and within selected subgroups of respondents, what are K-12 teacher *attitudes* about the potential or actual use of learning analytics as a viable strategy to improve instruction?

The four research questions correspond to the dimensions defined as part of a descriptive model proposed by Greller and Drachsler (2012) for use in conducting research about learning analytics across varied areas of interest.

Design Rationale

The design of this study is based on the concept of data-driven decision-making via exploratory-research methodologies. The area of focus evolved from the prediction of widespread use of learning analytics by classroom teachers during the early years of the 2010 decade. Review of current literature implied that use of learning analytics by classroom teachers is progressing at a much slower rate than expected (Dellinger, 2019; Joksimović et al., 2019; Michos et al., 2020). Hearing the voice of teachers providing opinions on awareness, usage, resources, and attitudes toward learning analytics will add to the current literature on implementation in K-12 classrooms. The data collection strategy evolved from a need for descriptive information about the topic; a survey methodology provided an avenue for input from a specifically defined population. Because of the funding models used for public education, a statewide survey strategy, across varied types of school districts, was implemented.

Role of the Researcher

When I entered the doctoral program in the summer of 2013, I had a decade of experience as a classroom teacher. I started my career as a lateral-entry teacher who was hired as one of three teachers to implement an early college on a community college campus. While skills acquired through the lateral-entry, teacher-training program proved to be valuable, I was struck by the noticeable gap between the practice of teaching that I experienced during the day and the theory of teaching that I studied during the evening.

During my first semester in the doctoral program, I was introduced to learning analytics. I discovered from the 2013 and 2014 Horizon Reports (Johnson et al., 2013; Johnson et al., 2014) that learning analytics was predicted to become widely used in K-12 classrooms within a few years. After finishing the coursework for the doctoral program, I found myself once again in front of a classroom. I began informally observing teacher practices and did not see any readily apparent examples of learning analytics. I began asking teachers if they used learning analytics; in most cases, those I asked were aware of learning analytics but were unable to explain what learning analytics could contribute to their teaching. My role in regard to the current study was one of striving to get the opinions from the "front-line" of those involved in the implementation of an educational innovation by designing a survey, collecting and analyzing survey data, and finally drawing conclusions about the status of learning analytics in the K-12 classrooms of North Carolina.

Ethical Issues

Since responses to the survey were submitted voluntarily and anonymously, ethics related to the privacy of the opinions was not an issue. Further, no information relating to specific students was requested. The most compelling decision related to selection of demographic information to be used for making comparisons across varied characteristics of respondents. Demographics related to size of school district (i.e., less than 5000, 5000 to 10,000, and more than 10,000 students), to level of teaching responsibility (i.e., elementary, middle and high school), and to location of the school (i.e., rural, suburban, urban) were identified. Further information was requested about respondent education and experience. No individual responses with profile information were considered in reporting results. Due to use of aggregated data analysis, no respondent could be re-identified. Considerable care was exercised, through the review process prior to distribution of the survey, to eliminate any ethical issues in administering the survey.

Participant Protocol

Participant Description

Public school teachers from all grade-levels of North Carolina classrooms were chosen to be participants in the collection of opinions about learning analytics; potential respondents, from among the approximately 99,000 public school teachers, were required to hold a current North Carolina teaching license. The choice of participants was driven by the projections of the 2013 and subsequent Horizon Report prediction on the adoption of learning analytics (Freeman et al., 2017; Johnson et al., 2013; Johnson et al., 2014). The Horizon Report predicted that learning analytics would be widely used within three years of their 2013 report; subsequent reports made similar predictions. A cross-sectional approach to data collection was followed in order to "provide a snapshot of the current behaviors, attitudes, and beliefs in a population" (Gay et al., 2012, p. 185).

Participant Selection

Survey validation procedures and IRB approval brought the timing of participant selection to June, 2020. The 2020 pandemic made a considerable difference in how data were to be collected. Prior to the pandemic, the research strategy involved coordinating with professional organizations and statewide conferences to get a broad representation of respondents through a personalized request for participation. Due to statewide quarantine and subsequent virtual learning modes in classrooms across the state of North Carolina, the planned strategy was no longer viable. Professional organizations focused on providing aid to classroom teachers in their online approaches to instruction and conferences were cancelled or postponed. Consequently, the Qualtrics (2014) panel system of providing survey participants was used.

> Qualtrics, the world's leading enterprise survey technology solution, has been providing online samples for over five years. Qualtrics partners with over 20 online panel providers to supply a network of diverse, quality respondents to our worldwide client base. Our Qualtrics Panels Team has completed over 15,000 projects across every industry vertical including travel, financial services, healthcare, retail, consumer goods, technology, and manufacturing both in the US and globally. (p.3)

Every project has an assigned project manager who closely monitors survey responses to ensure validity of the data. Initial screening included the following variables: resident of North Carolina, work in the education industry, role of K-12 teacher, and hold valid teaching license with NCDPI. The resultant participant pool yielded 85 respondents with the characteristics shown in

Table 1

Demographic Information

School Information					
School Type		District Location		District Size	
Elementary	29	Urban	17	<5000	22
Middle	29	Rural	28	5000-10000	21
High School	26	Suburb	39	>10000	41

Teacher Information					
High Stakes Teaching		Last Time in School		Education Types	
Always	31	0-5	36	Bachelor	85
Usually	31	6-10	18	Masters	33
Seldom	9	11-15	13	Doctorate	3
Never	13	16-20	7	Specialist	4
		21-25	3	Certificate	15
		26 or more	8	National Board	10

N=84 Employed; 1 not employed

Instrument Protocol

Data Source

Survey Items. The instrument used for the investigation of teacher use of learning analytics was a self-developed survey directed at collecting teacher opinions about and experiences with learning analytics in a classroom setting. “Because survey researchers often seek information that is not readily available, they usually need to develop an appropriate instrument (i.e., set of questions)…. If you want the appropriate answers, you have to ask the appropriate questions” (Gay et al., 2012, p. 184). While several surveys were described and/or included with research findings in the literature, none was similar enough to the current investigation to provide items or item protocols. Using entirely original questions, items were constructed to correspond to the research questions and related primarily to affective responses about awareness and use of learning analytics, observations about training and general attitudes about learning analytics. The completed survey included 32 items. In order to encourage a high level of honesty in the responses, specific directions were provided and the responses were anonymous. The introduction to the online survey included material typically placed in a cover letter for a survey and emphasized the importance and potential significance of the survey and the approximate length of time for completion of the survey. The Appendix includes the survey items along with a cover letter and instructions for completing the survey.

The survey was comprised of five sections: demographics preceding clusters on *awareness* of the concept of learning analytics, *usage* of learning analytics, *resources* for learning analytics, and *attitudes* about learning analytics. Survey items followed a structured, closed-ended format with each item of the survey comprised of a stem and response options. Some of the survey items used a rating scale, of 4=strongly agree, 3=agree, 2=disagree, and

1=strongly disagree. All respondents received identical questions plus subsets of questions determined by differentiated answers. Due to the many demands on teachers, time for completion of the survey was planned to take approximately 15 minutes. “As a general guideline, a questionnaire should be attractive, brief, and easy to respond to. Respondents are turned off by sloppy, crowded, misspelled, and lengthy questionnaires, especially ones that require long written responses to each question” (Gay et al., 2012, p.186). In a similar vein, Charles and Mertler (2002) suggested the following guideline for questionnaires development: “relatively few items should be included, directions should be simple, and responses should be easy to make; otherwise respondents will put the material aside and neglect to return it” (p.163).

Survey Validity. Content validity of the instrument was established by use of a panel of experts who reviewed each item for clarity in meaning and relevance for the appropriate research question. The panel, comprised of members of the dissertation committee, included experts in educational research design, learning analytics, and K-12 education. The process of review was iterative and terminated when the level of agreement concerning wording and content of items was consistent across the reviewers. The following relevant factors, taken from a longer checklist provided by Gay et al. (2012), formed the basis of item review.

- Make the questionnaire attractive and brief.
- Know what information you need and why.
- Include only information that relates to your study’s objectives.
- Collect demographic information, if needed.
- Focus items on a single topic or idea.
- Define or explain ambiguous terms.
- Word questions as clearly as possible.

- Avoid leading questions.
- Try to keep items and response options together.
- Subject items to pretest review of the questionnaire.

Several other similar sources were available for evaluating survey content and logistics (p.189). Gall et al. (2003) included 21 recommendations of similar nature; Fraenkel and Wallen (2006) suggested four criteria.

Further analysis occurred from a field test of the survey. An adaptation of cognitive interviewing (Drennan, 2003) was used to evaluate the survey on the basis of review by a small, convenience sample representing the population of North Carolina K-12 teachers. Cognitive interviewing involves interviewers asking survey respondents to think out loud as they go through a survey and to explain how they interpret each item. This allows understanding of the questionnaire from the respondents' perspectives rather than that of the researcher (p. 57).

The technique is useful for correcting problems with and improving the quality of survey questions. According to Beatty and Willis (2007), cognitive interviewing is typically conducted with a convenience sample of respondents similar to the population, is iterative in process in that items are modified after each interview, and 5 to 15 rounds of interviews are suggested. For the current research, a modified approach for cognitive interviewing was followed. The interviews included a group of six public school teachers, spaced across K-12 grade levels. For pre-testing a survey, Gay et al. (2012) stated that "having three or four individuals complete the questionnaire will help identify problems. Choose individuals who are thoughtful, critical, and similar to the intended research participants" (p. 189). During each interview, notes were taken as needed. After each interview, modifications to the survey occurred based on responses. A review by the expert panel occurred as the final step in the validation process.

IRB Procedure

Once the review of the survey items was completed by the panel of experts and the sample of typical recipients, an application to the Appalachian State University Institutional Review Board (IRB) was initiated. The resultant submission of the completed survey resulted in a decision of exempt and permission to proceed with data collection.

Data Collection

The data collection phase immediately followed the survey validation procedures and IRB approval. Qualtrics was used to format and distribute the survey items. Typically, Qualtrics has proven to be an efficient and trustworthy means of survey design and data collection. Reviewers of the survey reviewed the final version of the survey within the context of the online platform using Qualtrics.

Analysis Protocol

Data Coding

Typically, cross-sectional, survey research that investigates opinions and practices of respondents provide descriptive summaries of responses representing one point in time. Resultant findings can help to shape educational policy and initiatives with potential to improve existing conditions (Gall et al., 2003). According to Gay et al. (2012),

> …descriptive research …determines and describes the way things are. It may also compare how subgroups (such as males and females or experienced and unexperienced teachers) view issues and topics. …a high percentage of research studies rely on surveys for data and, as a result, are descriptive in nature. (p.159)

The Qualtrics platform provides a comma-separated value (CSV) file of raw data plus a summary of responses to each option for each item.

Data Analysis Protocol

Descriptive statistics were used to summarize the data from the survey responses of teachers concerning opinions about learning analytics in the context of K-12 classrooms. As is typical in the use of statistical strategies, the resulting data influenced the format of the techniques used to document opinions in regard to learning analytics. For example, response categories were combined, in a few cases, to provide groups of reasonable size to make meaningful comparisons.

For each item of the survey, the frequency and percentage of responses to each option were tabulated for the total number of respondents and for selected subgroups of respondents where appropriate. Using demographic data to create independent variables for comparisons, cross-tabulations were computed, where relevant, for each item. Demographic items include educational background of the teachers and characteristics of schools of their employment. To create groups of a reasonable size for comparisons, final delineation of the independent variables were based on the distribution of the respondents across options. Of particular interest was distribution of “No Opinion” in regard to selected independent variables. For example, did the location of the school affect the frequency of choosing “No Opinion” as a response? Cross-tabulations of demographic variables with survey items occurred for five of the six demographics—type of school, location of school, size of school, high stakes outcomes, and time since last college class. The demographic for degrees and certificates had insufficient variability to make cross-tabulations meaningful.

Trustworthiness

Review of quantitative data requires an understanding of the procedures for procurement of the data and review of the data analysis techniques. Any bias from the researcher arises at the instrumentation and interpretation stages of the study. The numbers, in a sense speak for themselves, and must be reviewed within the context of the respondent pool. In the current study, several revisions and subsequent review by experts in educational research techniques and cognitive interviews with individuals representing the target population occurred. Respondents were identified through the Qualtics Panel Process that obtains reliable respondent pools for survey research. Thorough review of the data was conducted and provided focus for the discussion and conclusions. Experts reviewed the interpretation of results for clarity and accuracy.

Chapter 4: Results

This investigation focused on validating the Horizon Report prediction that learning analytics would be widely used in K-12 classrooms by 2015 (Freeman et al., 2017; Johnson et al., 2013; Johnson et al., 2014). The following research questions guided survey results based on K-12 teachers' opinions in North Carolina concerning awareness, usage, resources, and attitudes about learning analytics as a viable strategy to improve instruction.

1. Across total respondents and within selected subgroups of respondents, what is the level of *awareness* by K-12 teachers of learning analytics as a viable strategy to improve instruction?
2. Across total respondents and within selected subgroups of respondents, how have K-12 teachers shown *usage* of learning analytics themselves or observed others using learning analytics as a viable teaching strategy to improve instruction?
3. Across total respondents and within selected subgroups of respondents, what types of *resources* have been available to K-12 teachers for gaining skill in using learning analytics as a viable strategy to improve instruction?
4. Across total respondents and within selected subgroups of respondents, what are K-12 teacher *attitudes* about the potential or actual use of learning analytics as a viable strategy to improve instruction?

The results of an online, fixed-option survey follow, differentiated by each research question. First, frequencies and percentages of responses to each of the 32 items are shown for the total group of respondents; second, the breakdowns of responses within subgroups are presented for several noteworthy comparisons.

Frequencies and Percentages of Total Respondents

Research Question 1: Awareness

Table 2 (items 3.1, 3.6, 3.7) provides responses concerning *awareness* of the use of data in the K-12 classroom and then, more specifically, the awareness of learning analytics. Nearly all the respondents were aware of the use of data for formative and summative decisions about student achievement whereas only 60% of the respondents admitted awareness of learning analytics either from within and/or outside their districts. That teachers were aware of formative and summative evaluations is to be expected due to statewide requirements on the use of test scores for accountability. Also, teachers often use formative evaluations with their classrooms to adjust their teaching strategies. That learning analytics is less recognized is likely due to variations across school districts on use of data for decision-making.

Table 3 (items 3.2- 3.5) provides responses by the subset of the respondents who indicated *awareness* of learning analytics from either within and/or outside their districts. Of those who were aware of learning analytics, most respondents indicated that their knowledge emerged from professional opportunities followed by school and district sources. College classes were least likely to be associated with awareness of learning analytics. Many teachers engage in professional opportunities, both required and voluntary, to increase their knowledge and skills regarding innovation. While teachers show awareness via school and district sources, such opportunities are typically geared toward policies and procedures within their schools and districts. College classes likely were least indicated due to the fact that only 42% of the respondents had been in college classes during the previous five years.

Table 2

Teacher Awareness of Learning Analytics

Trend	Within District		Outside District		Both		Neither	
	n	%	*n*	%	*n*	%	*n*	%
Learning Analytics	21	24.7	14	16.5	16	18.8	34	40.0
Formative Data Use	32	37.6	6	7.1	41	48.2	4	7.1
Summative Data Use	33	38.8	3	3.5	41	48.2	8	9.4

N=85

Table 3

Where Teachers Have Heard about Learning Analytics

Source	Strongly agree		Somewhat agree		Somewhat disagree		Strongly disagree	
	n	%	*n*	%	*n*	%	*n*	%
School Level	8	15.6	32	62.7	7	13.7	4	7.8
District Level	14	27.4	26	50.9	6	11.7	5	9.8
Professional Opportunities	14	27.4	31	60.8	4	7.8	2	3.9
Educational Opportunities	11	21.6	18	35.3	13	25.5	9	17.6

N=51

Research Question 2: Usage

Table 4 (item 4.1) provides survey results regarding *usage* of learning analytics in daily practice based on summaries from the total group of respondents. Usage of learning analytics in daily practice was reported to be quite high with 75% of the respondents strongly agreeing (21%) or somewhat agreeing (54%); disagreement was low with somewhat disagreeing (19%) and strongly disagreeing (6%) totaling only 25%. As part of their daily practice, many teachers are apparently using selected teaching materials and strategies, like those listed in the following two tables, which provide specific feedback about each student.

Table 5 (items 4.2 and 4.3) shows "types of use" and "strategies for use" of learning analytics based on responses of the 75% who reported using learning analytics in their daily practice. *Usage* of learning analytics for formative assessments and for setting goals and objectives were widely used followed closely by use of learning analytics for summative assessments and for differentiating instruction. Usage levels of specific strategies were, in general, somewhat lower. While the strategy of using learning analytics to monitor progress was quite high (85%), only two-thirds of the respondents used learning analytics for identifying at-risk students. The variability across the specific types of usage and strategies would indicate that teachers are selective in their choices of the types of data they use to enhance their teaching.

Table 6 (items 4.4 and 4.5) reports that approximately one-third of respondents were unsure of how many members of their school's faculty use learning analytics. From the remaining responses by those who made an estimate of use (i.e., did not select the response of unsure), about half estimated that 75% or more of the members of their school's faculty use learning analytics. Daily or weekly usage of learning analytics was indicated by most of the respondents who indicated an estimate of usage. Again, some use of data within the context of planning and providing instruction within the classroom is apparent across a large number of teachers.

Table 7 (items 4.6 and 4.7) results reveal that nearly one-third of the respondents were unsure of who among the typical stakeholders had access to learning analytics. Results indicate that teachers, followed by school and then district administrators, were more likely to have access to and then use learning analytics than were other school personnel, parents, and students. The hierarchy of access to learning analytics that resulted from the survey items seems to follow a typical pattern of teachers having greatest involvement with specific teaching strategies followed by oversight of administrators, and then support staff, and finally parents and students.

Table 4

Usage of Learning Analytics

Source	Strongly agree		Somewhat agree		Somewhat disagree		Strongly disagree	
	n	%	*n*	%	*n*	%	*n*	%
Daily Practice	18	21.2	46	54.1	16	18.2	5	5.9

N=85

Table 5

Learning Analytics Usage and Strategies

How teachers use learning analytics	*n*	%
Formative Assessments	53	82.8
Setting Goals/Objectives	50	78.1
Summative Assessments	44	68.8
Differentiating Instruction	44	68.8
Comparing/Contrasting	36	56.2
Making Predictions	32	50.0
Drawing Conclusions	32	50.0
Self-evaluation	32	50.0
Descriptive Data	22	34.4
Descriptive Assessments	18	28.1

N=64

Learning analytics strategies teachers use	*n*	%
Monitor Progress	54	84.4
Identify At-Risk Students	41	64.1
Personalize Learning	37	57.8
Modify Content Difficulty	36	56.2
Motivate Reaching Goals	33	51.6
Conduct Self-Assessments	31	48.4
Modify Content by Interest	25	39.1
Modify Negative Habits	16	25.0
Time Management Aid	13	20.3
Computer Score Essays	7	10.9

N=64

Table 6

Frequency of Use of Learning Analytics

How many teachers use learning analytics	*n*	%
100%	7	8.2
75% to 99%	23	27.1
50% to 74%	14	16.5
25% to 49%	9	10.6
0% to 24%	3	3.5
Unsure	29	34.1

N=85

How often teachers use learning analytics	*n*	%
Daily	15	17.6
Weekly	38	44.7
Monthly	10	11.8
A Few Times a Semester	5	5.9
A Few Times a Year	3	3.5
Unsure	14	16.5

N=85

Table 7

Access to Learning Analytics

Position	Access		Uses	
	n	%	*n*	%
Teachers	62	72.9	62	72.9
School Administrators	53	62.4	50	58.8
District Administrators	39	45.8	29	34.1
Counselors	30	35.3	24	28.2
Licensed Support Staff	28	32.9	28	32.9
Unsure	27	31.7	20	23.5
Parents	23	27.1	10	11.7
Students	22	25.8	16	18.8
Tech Support	12	14.1	12	14.1

N=85

Research Question 3: Resources

Table 8 (items 5.1-5.9) provides survey results regarding availability of *resources* based on summaries from the total group respondents. Resources were surveyed regarding availability of school or district positions assigned to work with teachers, professional development opportunities, and school strategies for involvement of teachers. Availability of personnel to support implementation of learning analytics was quite high—about 80% having technical support, about 70% having instructional design support, and about 60% having database support. Support for training on innovative classroom strategies was impressive with 75% indicating a positive response. However, support for specific training in learning analytics was reported by slightly less than half of the respondents and support for out-of-district training was reported by about one-third of the respondents. Dismal, as well, was availability of programs such as reduced teaching loads, committees, and forums to facilitate the implementation of learning analytics. The results concerning resources seem to be distinguished by funding scenarios. Instructional support positions and workshops on innovative strategies, possibly provided by staff, were widely available. Resources areas that might have needed budget support outside of staff positions were much less available.

Table 8

Training and Support

Issue	Yes		No		Unsure	
	n	%	*n*	%	*n*	%
Instructional Design Position	60	70.6	14	16.5	11	12.9
Technical Issues Position	69	81.2	12	14.1	4	7.7
Student Data Base Position	50	58.8	11	12.9	24	28.2
Innovative Strategies Workshops	64	75.3	12	14.1	9	10.6
Learning Analytics Workshops	38	44.7	18	21.9	29	34.1
Out-of-District Workshops	30	35.2	26	30.6	29	34.1
Reduced Teaching Loads	11	12.9	54	63.5	20	23.5
Committees	34	40.0	26	30.6	25	29.4
Forums	27	31.8	31	36.5	27	31.8

N=85

Research Question 4: Attitudes

Table 9 (items 6.1-6.9) provides survey results regarding *attitudes* about learning analytics based on summaries of the total group of respondents. Of the nine items related to attitudes, six revealed highly positive attitudes toward learning analytics: useful online materials, ability to benefit from training, desire to know more, need for computerization, great potential, and more face-to-face time. Three of the items had mixed results: violation of privacy, expense, and need for computer-based instruction. Privacy is a huge issue for teachers due to the threat of litigation, expense is another huge issue since funds are typically dedicated to salaries and to infrastructure, and fully computerizing instruction is seen as a threat to the positives of interacting with students or the threats to job security.

Table 9

Attitudes about Learning Analytics

Issue	Strongly agree		Somewhat agree		Somewhat disagree		Strongly disagree	
	n	%	*n*	%	*n*	%	*n*	%
Online Materials	36	42.4	45	52.9	2	2.4	2	2.4
Background/ Ability	34	40.0	45	52.9	4	4.7	2	2.4
Instructional Strategy	37	43.5	41	48.2	3	3.5	4	4.7
Violate Privacy	7	8.2	25	29.4	42	49.4	11	12.9
Too Expensive	7	8.2	31	36.5	38	44.7	9	10.6
Computer Based	8	9.4	27	31.8	38	44.7	12	14.1
Resources	26	30.1	55	64.7	4	4.7	0	0.0
Great Potential	30	35.3	47	55.3	6	7.1	2	2.3
More Face-to-Face	36	42.3	44	51.8	2	2.4	3	3.5

N=85

Frequency and Percentages within Subgroups

Research Question 1: Awareness

Tables 10 through 12 include several comparisons of items relating to *awareness* of learning analytics by selected subgroups of respondents. The comparisons focus on awareness with demographics related to type of school, size of school, and years since earning hours in a college or university.

The first comparison shown in Table 10 (item 2.2 with 3.1) includes opinions by the total group of respondents. Breakdowns using type of school are compared with the responses from the item about awareness of the "educational trend referred to as learning analytics." By combining the replies of "within district" with "from both within and outside my district," approximately two-thirds of the high school teachers had heard about learning analytics from within their district compared to only 30% to 40% from elementary and middle schools. High school classrooms typically provide more opportunities for independent and differentiated learning than do lower grade levels. Likely, high school teachers have more opportunity to adopt data-driven strategies than do elementary and middle schools where more classroom control is typically needed.

The second comparison shown in Table 11 (item 2.4 with 3.2 and 3.3) reviews responses from the 51 teachers who indicated that they were aware of an "educational trend referred to as learning analytics." Size of school is compared with two items about where teachers obtain information about learning analytics. Most teachers from districts with less than 5000 students indicated that they "heard about using learning analytics in their classrooms" from sources at both the district and school levels. The pattern changed slightly in looking at the two larger categories of school-district size. More teachers from districts with 5000 to 10,000 students heard from the district level whereas more teachers from districts with 10,000 or more students heard from the school level. No clear pattern of size of school in relationship to disseminating information emerged. Possibly, information that is shared via school and district sources is somewhat standardized for all grade levels across the state.

The third comparison shown in Table 12 (item 2.6 with 3.5) reviews responses from the 51 teachers who indicated that they were aware of an "educational trend referred to as learning analytics." Results reveal a trend across the three levels of time since earning hours from a college or university. Respondents who have had more recent educational opportunities seemed to have heard more about learning analytics than those who have had less recent educational opportunities. The finding is expected since college and university classes will typically cover recent innovations related to teaching and learning strategies. Learning analytics has been on the radar for teaching innovation for 10+ years so having at least an introduction to the concept via college and university classes should occur even in programs with less emphasis on technological innovation.

Table 10

Cross-tabulation for Awareness with Type of School

Aware of educational trend	Elementary School		Middle School		High School	
	n	%	*n*	%	*n*	%
From within my district	6	20.7	7	16.5	8	30.8
From outside my district	6	20.7	5	7.1	3	11.5
From both	6	20.7	2	3.5	8	30.8
From neither	11	37.9	15	51.7	7	26.9
Total	29	100.0	29	100.0	26	100.0

N=84

Table 11

Cross-tabulation for Awareness with Size of School

District level information	<5000		5000-10000		>10000	
	n	%	*n*	%	*n*	%
Strongly agree	4	26.7	1	6.7	3	14.3
Somewhat agree	10	66.7	12	80.0	10	47.6
Somewhat disagree	1	6.7	0	0.0	6	28.6
Strongly disagree	0	0.0	2	13.3	2	9.5
Total	15	100.0	15	100.0	15	100.0
	<5000		5000-10000		>10000	
	n	%	*n*	%	*n*	%
Strongly agree	5	33.3	2	13.3	7	33.3
Somewhat agree	9	60.0	9	60.0	8	38.1
Somewhat disagree	1	6.7	1	6.7	4	19.0
Strongly disagree	0	0.0	3	20.0	2	9.5
Total	15	100.0	15	100.0	15	100.0

N=51

Table 12

Cross-tabulation for Awareness with Educational Opportunities

Awareness Through Classes	0 to 5 years		6 to 10 years		11+ years	
	n	%	*n*	%	*n*	%
Strongly agree	7	30.4	3	25.0	1	6.2
Somewhat agree	9	39.1	4	33.3	5	31.2
Somewhat disagree	5	21.7	3	25.0	5	31.2
Strongly disagree	2	8.7	2	16.7	5	31.2
Total	23	100.0	12	100.0	16	100.0

N=51

Research Question 2: Usage

Tables 13 and 14 include several comparisons of items relating to *usage* of learning analytics by selected subgroups of respondents. The comparisons focus on usage with demographics related to type of school, location of school, and size of school.

The first group of comparisons shown in Table 13 (Items 2.2, 2.3, and 2.4 with 4.1) review the item about "use of learning analytics in my daily practice." Agreement is high that teachers are using learning analytics with slight differences in frequency across school classifications. High school teachers, when compared to middle and elementary teachers, are slightly more likely to use learning analytics. Suburban teachers, when compared to rural and urban teachers are slightly more likely to use learning analytics. Teachers at the smallest districts, when compared to larger districts, are more likely to use learning analytics. High school teachers in suburban districts with less than 5000 students appear to use learning analytics more frequently than those representing the other combinations of demographics. The dynamics of interaction among teachers would likely affect use of learning analytics among teachers at different sizes of schools. Some schools create work clusters for those who are teaching the same classes to the same grade-levels. Smaller school districts might develop greater community sharing of ideas and resources related to innovation.

Table 13

Cross-tabulation for Usage with School Classifications

Use in daily practice	Elementary School		Middle School		High School	
	n	%	n	%	n	%
Strongly agree	4	13.8	7	24.1	7	26.9
Somewhat agree	17	58.6	13	44.8	16	61.5
Somewhat disagree	4	13.8	8	27.6	3	11.5
Strongly disagree	4	13.8	1	3.4	0	0.0
Total	29	100.0	29	100.0	26	100.0
	Urban		Rural		Suburban	
	n	%	n	%	n	%
Strongly agree	4	23.5	7	17.9	9	23.1
Somewhat agree	8	47.1	13	53.6	23	59.1
Somewhat disagree	3	17.6	8	25.0	5	12.2
Strongly disagree	2	11.8	1	3.6	2	5.1
Total	17	100.0	29	100.0	39	100.0
	<5000		5000-10000		>10000	
	n	%	n	%	n	%
Strongly agree	5	27.7	4	19.0	9	22.0
Somewhat agree	14	63.6	11	52.4	21	51.2
Somewhat disagree	3	13.6	4	19.0	8	19.5
Strongly disagree	0	0.0	2	9.5	3	7.3
Total	22	100.0	21	100.0	41	100.0

N=84

The second group of comparisons shown in Table 14 (Items 2.2, 2.3, and 2.4 with 4.1) review the item about "use of learning analytics by members of your school's faculty." Across the comparisons based on the three demographic items, the choice of the "unsure" response ranges from about 25% to 50%. When the unsure responses are removed from the comparisons, then perception of usage of learning analytics by the school's faculty is approximately 50%. Elementary teachers, urban teachers, and teachers from schools with greater than 10,000 students appear to be the most unsure of their colleagues use of learning analytics. On the other hand, middle school teachers, urban teachers, and teachers from schools with less than 5000 students were less likely to select the "unsure" response. Once again, communication about teaching strategies might be more common in smaller schools than in larger schools.

Comparison of the profiles from Tables 13 and 14 does show one consistency. In general, teachers in suburban districts with less than 5000 students showed the strongest profile for use of learning analytics in their daily practice. The same profile emerged for those who indicated an estimate of use of learning analytics by their colleagues. Perhaps, teachers in suburban districts with less than 5000 students have greater awareness of the concept and are more likely to use data for decision making.

Table 14

Cross-tabulation for Usage by Colleague with School Classifications

Using learning analytics	Elementary School		Middle School		High School	
	n	%	n	%	n	%
100%	3	10.3	1	3.4	3	11.5
75% to 99%	4	13.8	13	44.8	6	23.1
50% to 74%	5	17.2	4	13.8	5	19.2
25% to 49%	2	6.9	3	10.3	4	15.4
0% to 24%	2	6.9	1	3.4	0	0.0
Unsure	13	44.8	7	24.1	8	30.8
Total	29	100.0	29	100.0	26	100.0
	Urban		Rural		Suburban	
	n	%	n	%	n	%
100%	2	11.8	2	7.1	3	7.7
75% to 99%	4	23.5	7	25.0	12	30.8
50% to 74%	1	5.9	5	17.9	8	20.5
25% to 49%	1	5.9	2	7.1	6	15.4
0% to 24%	1	5.9	2	7.1	0	0.0
Unsure	8	47.1	10	35.7	10	25.6
Total	17	100.0	28	100.0	39	100.0
	<5000		5000-10000		>10000	
	n	%	n	%	n	%
100%	1	4.5	0	0.0	6	14.6
75% to 99%	6	27.3	7	33.3	10	24.4
50% to 74%	6	27.3	4	19.0	4	9.8
25% to 49%	3	13.6	2	9.5	4	9.8
0% to 24%	0	0.0	2	9.5	1	2.4
Unsure	6	27.3	6	28.6	16	39.0
Total	22	100.0	21	100.0	41	100.0

N=84

Research Question 3: Resources

Tables 15 and 16 include several comparisons of items relating to *resource* availability by selected subgroups of respondents. The comparisons focus on resources related to staff positions and to training with demographics related to type of school, location of school, and size of school.

The first comparison in Table 15 (Items 2.4 with 5.1, 5.2, and 5.3) reviews size of school with availability of instructional design, technical, and database consultants. The response in regard to technical consultants, while high overall, revealed similar, very positive response for the smaller and middle sizes of schools and a lower response for the largest districts. Instructional design assistance, while lower, was still at about 75% overall but slightly lower for the largest district size. Database assistance had less availability especially with the smallest and the largest of the three school size categories. In general, the largest districts seemed to have less assistance provided in consulting positions. The resources within large districts should be greater than those in smaller districts due to the per pupil formulas for funding. The data do not support this supposition. Perhaps, teachers in larger districts rely more on each other for trouble-shooting. With larger faculties, more diversity in skill is likely. Plus, asking a colleague for assistance does not require the official, and maybe annoying, paper trail.

The second comparison shown in Table 16 (Items 2.2, 2.3, and 2.4 with 5.5) deals with professional development training in learning analytics across three school classifications. For the most part, about one-third of the respondents were unsure about "professional development training for teachers on the use of learning analytics." High schools in rural areas with less than 5000 students represent the only profile where professional development training on learning analytics was rated at slightly over 50%. Perhaps, small rural schools provide more training opportunities in general due to their more remote locations and high school teachers are more likely to show interest in using data to facilitate their classroom instruction. Small schools may need more training to keep faculties up-to-date on a variety of innovations since the levels of expertise among colleagues are limited by size. As suggested by several earlier comparisons, high school teachers might see their students as better target for data-based learning.

Table 15

Cross-tabulation for Resources with Size of School

Instructional Support	<5000		5000-10000		>10000	
	n	%	n	%	n	%
Yes	16	72.7	16	76.2	27	65.9
No	3	13.6	2	9.5	9	22.0
Unsure	3	13.6	3	14.3	5	12.2
Total	22	100.0	21	100.0	41	100.0
	<5000		5000-10000		>10000	
	n	%	n	%	n	%
Yes	20	90.9	18	85.7	30	73.2
No	1	4.5	2	9.5	9	22.0
Unsure	1	4.5	1	4.8	2	4.9
Total	22	100.0	21	100.0	41	100.0
	<5000		5000-10000		>10000	
	n	%	n	%	n	%
Yes	11	50.0	15	71.4	24	58.5
No	4	18.2	1	4.8	6	14.6
Unsure	7	31.8	5	23.8	11	26.8
Total	22	100.0	21	100.0	41	100.0

N=84

Table 16

Cross-tabulation for Resources with School Classifications

Professional Development Training	Elementary School		Middle School		High School	
	n	%	n	%	n	%
Yes	14	48.3	10	34.5	14	53.8
No	4	13.8	9	31.0	5	19.2
Unsure	11	37.9	10	34.5	7	26.9
Total	29	100.0	29	100.0	26	100.0
	Urban		Rural		Suburban	
	n	%	n	%	n	%
Yes	4	23.5	18	64.3	16	41.0
No	6	35.3	2	7.1	10	25.6
Unsure	7	41.2	8	28.6	13	33.3
Total	17	100.0	28	100.0	39	100.0
	<5000		5000-10000		>10000	
	n	%	n	%	n	%
Yes	14	63.6	8	38.1	16	39.0
No	5	22.7	4	19.0	9	22.0
Unsure	3	13.6	9	42.9	16	39.0
Total	22	100.0	21	100.0	41	100.0

N=84

Research Question 4: Attitudes

Tables 17 through 19 include several comparisons of items relating to *attitudes* by selected subgroups of respondents. The comparisons focus on attitudes with demographics related to type of school, location of school, and size of school. Due the high positive responses for six of the nine items concerning attitude, and consequently lack of variability across groups, the comparisons focus on items relating to privacy, expense, and computer-based instruction. For the three items of interest, note that a response of agreement reflects a negative attitude and that a response of disagreement reflects a positive attitude.

The first comparison in Table 17 (Items 2.2, 2.3, and 2.4 with 6.4) reviews privacy. While the responses predominantly reflect disagreement that there "is too much potential to violate privacy," elementary and middle school teachers, rural and suburban teachers, and teachers from the two larger of the district sizes find the concept slightly more worrisome.

The second comparison in Table 18 (Items 2.2, 2.3, and 2.4 with 6.5) reviews expense. Opinions show considerable variability regarding learning analytics "being too expensive for individual teacher use." Elementary school teachers are in greatest agreement that the expense is too high followed by middle school and then high school teachers. Rural and suburban teachers show considerably more agreement that the expense is too high than do urban teachers. Size seems to have less variability but does reveal greater agreement that the expense is too high by the respondents from the two larger categories of district size. In general, high school teachers from urban areas with less than 5000 students are less critical of the costs associated with learning analytics. The resultant outcome combining urban areas with small size is inconsistent with reality. Typically, urban areas are larger in size than rural and suburban districts. A larger sample size for the study, in general, would likely add clarification.

The third comparison in Table 19 (Items 2.2, 2.3, and 2.4 with 6.6) reviews the need for computer-based instruction. Again the patterns are varied with elementary and middle school teachers showing considerably more agreement than high school teachers that "learning analytics will not be viable until all instruction is computer based." Type of district shows a more gradual trend with teachers from rural and suburban schools showing more agreement than those from urban schools. Size of district shows more agreement by teachers from the 5000 to 10,000 size category with a large drop in agreement by teachers from the smallest and largest size categories. In general high school teachers from urban districts of small or large size are less critical of the need for computerization. The trend for high schools teachers showing greater interest in use of learning analytics is holding up once again. Greater cognitive maturity of students and perhaps, larger class sections, are a stimulus. Plus, urban districts, based on per pupil funding, are likely to have more resources for innovation plus, due to potential markets, sales representatives are more likely to provide support for innovation.

Table 17

Cross-tabulation for Privacy with School Classifications

Violation of privacy	Elementary School		Middle School		High School	
	n	%	n	%	n	%
Strongly agree	4	13.8	3	10.3	0	0.0
Somewhat agree	8	27.6	9	31.0	8	30.8
Somewhat disagree	14	48.3	16	55.2	11	42.3
Strongly disagree	3	10.3	1	3.4	7	26.9
Total	29	100.0	29	100.0	26	100.0
	Urban		Rural		Suburban	
	n	%	n	%	n	%
Strongly agree	0	0.0	3	10.7	4	10.3
Somewhat agree	4	23.5	7	25.0	14	35.9
Somewhat disagree	8	47.1	15	53.6	18	46.2
Strongly disagree	5	29.4	3	10.7	3	7.7
Total	17	100.0	28	100.0	39	100.0
	<5000		5000-10000		>10000	
	n	%	n	%	n	%
Strongly agree	2	9.1	2	9.5	3	7.3
Somewhat agree	4	18.2	6	28.6	15	36.6
Somewhat disagree	14	63.6	10	47.6	17	41.5
Strongly disagree	2	9.1	3	14.3	6	14.6
Total	22	100.0	21	100.0	41	100.0

N=84

Table 18

Cross-tabulation for Expense with School Classifications

Too expensive for teachers	Elementary School		Middle School		High School	
	n	%	n	%	n	%
Strongly agree	4	13.8	2	6.9	1	3.8
Somewhat agree	14	48.3	11	37.9	6	23.1
Somewhat disagree	9	31.0	14	48.3	14	53.8
Strongly disagree	2	6.9	2	6.9	5	19.2
Total	29	100.0	29	100.0	26	100.0
	Urban		Rural		Suburban	
	n	%	n	%	n	%
Strongly agree	0	0.0	5	17.9	2	5.1
Somewhat agree	3	17.6	11	39.3	17	43.6
Somewhat disagree	10	58.8	10	35.7	17	43.6
Strongly disagree	4	23.5	2	7.1	3	7.7
Total	17	100.0	28	100.0	39	100.0
	<5000		5000-10000		>10000	
	n	%	n	%	n	%
Strongly agree	2	9.1	3	14.3	2	4.9
Somewhat agree	6	27.3	7	33.3	18	43.9
Somewhat disagree	11	50.0	9	42.9	17	41.5
Strongly disagree	3	13.6	2	9.5	4	9.8
Total	22	100.0	21	100.0	41	100.0

N=84

Table 19

Cross-tabulation for Computer Use with School Classifications

Computer-based instruction	Elementary School		Middle School		High School	
	n	%	n	%	n	%
Strongly agree	5	17.2	2	6.9	1	3.8
Somewhat agree	10	34.5	12	41.4	5	19.2
Somewhat disagree	10	34.5	13	44.8	14	53.8
Strongly disagree	4	13.8	2	6.9	6	23.1
Total	29	100.0	29	100.0	26	100.0
	Urban		Rural		Suburban	
	n	%	n	%	n	%
Strongly agree	0	0.0	3	10.7	5	10.7
Somewhat agree	5	29.4	8	28.6	14	28.6
Somewhat disagree	6	35.3	14	50.0	17	50.0
Strongly disagree	6	35.3	3	10.7	3	10.7
Total	17	100.0	28	100.0	39	100.0
	<5000		5000-10000		>10000	
	n	%	n	%	n	%
Strongly agree	2	9.1	4	19.0	2	4.9
Somewhat agree	5	22.7	9	42.9	13	31.7
Somewhat disagree	12	54.5	6	28.6	19	46.3
Strongly disagree	3	13.6	2	9.5	7	17.1
Total	22	100.0	21	100.0	41	100.0

N=84

Overall, the comparisons across school types indicate that high school teachers from urban districts with the smallest enrollments find concerns about privacy, cost, and computer-based instruction less worrisome.

Summary

The results of the survey revealed a number of findings that contradict the strong prediction by the 2013 Horizon Report that learning analytics would be widely used within a few years. While many strategies have been adopted and many products are in use, the implementation is fragmented and irregular. That teachers could not consistently indicate that they and their colleagues are actively using learning analytics indicates a need for more leadership and funding opportunities to advance the practice. In general, teachers from high schools, suburban schools, and smallest size schools were more likely to provide more positive responses concerning awareness, usage, resources, and attitudes. While the survey did not investigate the reasons for the replies, in general, the higher level of cognitive maturity of high school students when compared to elementary-level students and the more homogeneous populations of suburban districts when compared to the diversity generally associated with urban and rural schools likely give more time and resources to innovative instructional approaches. Differences in responses due to size of district were less consistent than the comparison across level of teaching and location of schools.

Chapter 5: Conclusions

This investigation focused on the responses of K-12 teachers from North Carolina regarding their opinions about awareness, usage, resources, and attitudes concerning learning analytics. The results contribute to the evaluation of the validity of the Horizon Report predictions for implementation of learning analytics in K-12 schools (Freeman et al., 2017; Johnson et al., 2013; Johnson et al., 2014) as well as document the role of teachers in the adoption of learning analytics in the classroom. The voice of the teacher, a major stakeholder in the implementation of innovation in K-12 classrooms, is heard.

An online survey composed of 32 fixed-response items was used for data collection via the Qualtrics platform. The literature suggests that surveys be clearly stated, easy to complete, and have a short response time. The conceptual framework of exploratory research, within the context of evidence-based decision-making, represented such a philosophy and provided meaningful insights and comparisons. Within a conceptual framework of conducting research specifically about learning analytics (Drachsler & Greller, 2012), survey items reflected the suggested categories of stakeholders, objectives, data, method, constraints, and competence through the choice of teachers as the survey respondents and survey items related to awareness, usage, resources, and attitudes.

While many approaches to such an investigation are plausible, the current investigation carried the delimitation of focusing on the voices of classroom teachers in North Carolina through a self-report methodology. A self-report methodology leaves the interpretation of terminology to the backgrounds and experiences of the respondents. In the case of the current study, some confusion might have evolved due to the formality of the definition given initially and the varied types of applications that often fall within the context of learning analytics. The primary limitations of the study involved a convenience sample with voluntary participation by the respondents and a data-gathering instrument that had not been previously used. The 2020 pandemic added further to the limitations due to the difficulty of finding an appropriate data collection strategy and the resultant small level of participation. A larger sample size of K-12 teachers in North Carolina would have added considerably to the generalizability of the results.

Considering the numerous publications and conferences related to learning analytics and the variety of related products that have been generated over the past decade, this study of teacher impressions of learning analytics at the K-12 level in North Carolina is disheartening. Likely, many K-12 teachers in North Carolina have heard the buzzword, have reviewed products and strategies related to learning analytics, and have acquired many relevant technical skills, but they have not gained a cohesive overview of the potential of the concept. The literature review revealed that the concept of learning analytics is seen with much favor yet is associated with frustration over implementation. Respondents did reveal some awareness and usage of learning analytics, in some cases did have access to support personnel and other resources, and did reveal a very positive attitude toward the concept.

The following sections explore the research findings in an attempt to give perspective to the current status of learning analytics as expressed by teachers themselves. First, a discussion of findings is presented in alignment with the four research questions, in relation to the literature review, and with consideration of gaps in the current literature. Finally, implications of findings in relation to current practice and suggestions for future research are presented.

Discussion

Awareness

The finding that 40% of the K-12 respondents indicated no awareness of learning analytics, based on its formal definition as stated in the survey instructions, is stunning. As early as 2007, Campbell et al. used the term "buzz word" in relation to learning analytics. Later, Drachsler and Greller (2012) referred to "much buzz." More recently, learning analytics was called a "major component" in instruction (Selwyn, 2019) and its popularity among educators was noted (Joksimovic et al., 2019). Professional opportunities to become involved with learning analytics have proliferated via "peer –reviewed" conferences and scholarly articles. Products to support learning analytics are numerous. While survey responses about use of data for formative and summative assessments revealed a high level of awareness, the "buzz word" of learning analytics was less recognizable by K-12 teachers. High school teachers, likely due to the cognitive maturity of their students, and those from the smaller schools, possibly due to their communication patterns, showed slightly higher awareness of learning analytics. More noteworthy, however, was the result showing that those who had recently completed college courses indicated higher awareness.

Much scholarly literature with articles on applications of learning analytics in higher education is available. For example, Drachsler and Greller (2012), Siemens (2013), and Ifenthaler (2017) are names that have had a presence in the higher education literature during the past decade. Dellinger concluded as recently as 2019 in the discussion of his research that "while there has been a growth of research on the learning analytics adoption process in higher education context, little has taken place in K-12" (p.74). Due to the maturity level of students in higher education, the self-motivation associated with many instructional strategies that use learning analytics tools is more likely. Elementary school students have different needs for structure in learning than older students and, therefore, might be less cognitively prepared for some approaches to learning analytics. Still, younger students can benefit from many of the tools of learning analytics that monitor and guide instruction but possibly not the self-paced, individualized strategies.

Much of the literature implies that educators, in general, have an awareness of learning analytics. For example, Dawson et al. (2019) have commented that “it is commonly noted that learning analytics (LA) has the potential to address many of the challenges confronting contemporary education” (p. 446). Furthermore, according to Sun et al. (2016), “ school leaders are relying more and more on evidence, and thus, increasingly use student and school data to inform decision-making” (p.93). Even with the greater probability of awareness among higher education practitioners, the expectation of greater awareness among K-12 educators seems plausible. In my own educational experience, I had ample opportunity to take classes in business analytics and learning analytics. Whether other programs have such options is unknown. One of the considerations with advancing learning analytics in K-12 contexts might be the interests and backgrounds of the professors of education and the preparation of licensed teachers whose formal education culminated prior to the decade of 2010. According to Aldunate and Nussbaum (2013), “early adopters exhibit a higher likelihood of adopting technology, almost independent of the level of complexity of the technology” (p.11). Consequently, teachers whose preparation included some focus on use of data for decision-making might be more likely to adopt innovative technologies as they proceed through their careers.

Usage

Stevenson (2017) has made the following observation about the teachers' workloads: "Teachers face considerable and increasing pressure in their working lives. Labor intensification compels teachers to work faster, harder, and longer."(p. 537). A reasonable implication is that finding time to master new skills, especially those that include the four-letter word "data," is difficult to accomplish within the parameters of teachers' job responsibilities. Furthermore, from the literature review, usage of learning analytics by K-12 teachers is related to leadership and how the district and school leaders promote the incorporation of innovative strategies within existing structures. Sun et al. (2016) commented that "there is a lack of consensus regarding how school leaders should promote teachers' use of student data" (p. 94). Priority in the use of data is generally geared toward required reporting obligations (Herold, 2016); use of data to improve instruction might be viewed as less critical.

In spite of possible workload factors in adopting learning analytics strategies and the need for leadership guidance, three-fourths of the respondents did indicate that they use learning analytics in their daily practice. Table 5 lists the numbers of teachers who reported using specific tools and strategies related to learning analytics. While similar patterns of usage were distributed across the three levels of schools, high school teachers did reveal an overall higher usage again raising the issue of cognitive maturity. Also, usage was found to be higher in suburban schools than in rural and urban schools, possibly due to perception by some that suburban communities have less need to focus on inequities among their populations and have more interest and resources to pursue innovation.

Usage was further investigated by asking respondents to estimate use by other teachers. While teachers with an opinion indicated some usage by colleagues, about one-third of the respondents indicated that they were “unsure.” The level of uncertainty of usage of learning analytics by colleagues might reflect lack of cohesive strategies within school systems in regard to systematic implementation.

A primary factor to consider in usage of learning analytics is the different focus of formative versus summative assessments. Responses revealed estimates that teachers and school administrators had high access to and often used learning analytics. Due to the emphasis from state and local mandates about accountability, data are typically used on an annual basis in a summative way. With a thorough understanding of learning analytics, teachers might realize that data can be used to improve instruction through an ongoing, formative approach. Teachers, who indicated use of learning analytics in their daily practice, indicated their methods of use and their strategies for use of selected applications of learning analytics. Of those who use learning analytics, 82% indicated that formative assessments were part of their routine. Further, 84% of the users of learning analytics indicated monitoring progress as a frequent strategy. Many of the other uses and strategies were not as popular.

Interestingly, the “awareness” of learning analytics (see Table 2) was reported to be only around 60% whereas ”usage” was reported to be about 75% (see Table 4). Obviously, one might expect that respondents who reported usage of learning analytics would also have reported awareness of the concept. A cross-tabulation of the two items revealed no discernable pattern to explain the difference (see Table 20). The discrepancy between responses relating to awareness and usage would point to some issues with the meaning of the concept of learning analytics. The survey item on awareness was associated with a formal definition of learning analytics whereas the survey item related to usage was associated with several subsequent items about specific instructional uses and strategies. Could the discrepancy have occurred due to the formality and generalization of awareness and the specificity of usage? Teachers might have heard the "buzz word" without realizing what it actually meant.

Table 20

Cross-tabulation for Awareness with Usage

Usage of learning analytics	From within my district		From outside my district		From both		From neither	
	n	%	n	%	n	%	n	%
Strongly agree	7	33.3	0	0.0	0	12.5	9	26.5
Somewhat agree	12	57.1	9	64.3	9	62.5	15	44.1
Somewhat disagree	2	9.5	4	28.6	4	18.8	7	20.6
Strongly disagree	0	0.0	1	7.1	1	6.3	3	8.8
Total	21	100.0	14	100.0	16	100.0	34	100.0

N=85

Resources

Literature on learning analytics is full of references to issues of limited resources (Arnold, 2014; Pearce & Cleary, 2016). Plus, much available research reveals that leadership at state, district, and school levels is crucial to creating an environment for innovation (Cho & Wayman, 2014; Sun et al., 2016). Infrastructure is critical. According to Dellinger (2019), lack of infrastructure results in "…not having enough time to use it effectively, not having it in real-time, having to look for it in a number of disconnected systems..." (p.80). Time and funding are the culprits. Local funding is often consumed by salaries and the safe and functional maintenance of physical structure. Support personnel are needed to keep systems functioning. Training, including both time and resources, is needed to update teacher skills. Programs and policies within the school are needed to facilitate and recognize progress.

The procurement of grant funds from federal and state governments and private sources is a possible solution to the funding issue.

> …given the constrained nature of K-12 system technology budgets, Federal and State governments must seriously consider direct support for the delivery of educational

> technology applications services and devices for K-12 schools…. Federal government and/or state funding could reduce the technology supply constraints that presently exist and could enable education administrators to focus on the systematic selection and implementation of educational technology rather than having to scramble to fund such technology on a piecemeal basis…. In addition, the participation and contribution of the private sector as a key partner in this endeavor is critically important for the development of new and more advanced educational technologies. (Pierce & Cleary, 2016, p. 877)

Survey findings about resources follow with discussion focused on support personnel, training, and school structure.

Teachers were surveyed regarding the availability of support personnel in areas of technical issues, instructional design, and data base access. In general, the largest districts seem to have less assistance provided by personnel in support positions. From survey results, the staff position with highest availability for consultation with teachers related to technical issues. Computer systems malfunction often and having some resources for repair is mandatory, but only 80% of the respondents indicated availability of a position related to technical expertise. Instructional design, or learning design as it is often called (Ifenthaler, 2017a; 2017b), is essential to insure personalization of instruction within the context of an individualized curriculum. Approximately 70% of the respondents reported availability of instructional design assistance. Of the three positions, data base support, where critical data on personalization of instruction resides, was seen as least available at 60%. Learning analytics requires all three types of support personnel to be readily available if teachers, who often lack technical skills, are to implement learning analytics in their classrooms. Some literature suggests that teachers can become experts in learning analytics in a qualitative sense (Siemens & Long, 2011). They do not have to be statisticians or data base managers if appropriate support personnel are available.

Training is needed to advance skills of teachers who did not study learning analytics during their teacher preparation. Training can be in many forms from on-site, to professional workshops, to certificate programs from higher education. Respondents indicated the availability of workshops on innovative strategies but revealed almost no workshops on learning analytics or opportunities to attend out-of-district workshops. The smallest of the districts did report greater availability of opportunities for training in learning analytics. In general, however, the daily routine of teachers is typically too crowded with teaching to allow for independent pursuit of intensive instructional goals. A definite need exists to provide training in learning analytics without an added workload burden (Chiu, 2017).

Hodges and Prater (2014) labeled lack of resources as a first-order barrier to technology innovation in schools. Appropriate strategies to foster innovation in schools include reduced teaching loads, committees for collaboration, and forums to request input and ideas from others. Survey responses revealed availability of these strategies to be quite limited. In fact, reduced teaching loads were identified by only 13% of the respondents. Typically, implementation of innovative strategies is facilitated by leadership and time, thus, providing another rationale for obtaining outside finding to advance innovative learning strategies.

Attitudes

Hodges and Prater (2014), having labeled lack of resources as a first-order barrier to innovation, listed attitudes and beliefs of teachers as a second-order barrier to innovation. “It is clear that teachers’ beliefs of the value and perceived usefulness of various technologies are important elements to consider when adopting technologies for teaching and learning” (p.71).

Attitudes, as reported in the literature on learning analytics, reflect very positive impressions of the concept. Descriptions of the benefits of learning analytics just make sense. However, the logistics are overwhelming unless adequate resources exist (Dawson, et al., 2019; Pierce & Cleary, 2016; Selwyn, 2019).

Findings related to six of the nine survey items about attitude revealed a high level of positive agreement on the importance and usefulness of learning analytics. For example, 93% of the respondents felt that they had the background and ability to adopt learning analytics in their teaching; 87% would like to know how to incorporate learning analytics into their classrooms. In comparison, the remaining three items revealed relatively negative attitudes concerning privacy, expense, and computer use. Privacy, a frequent issue of concern in the literature, was seen as problematic by 37% of the respondents; expense, another frequent issue of concern in the literature, was seen as problematic by 45% of the respondents; and necessity of computer-based instruction, also a frequent issue of concern in the literature, was seen as problematic by 41% of the respondents. Some consistency of patterns relating to attitude were evident across demographic characteristics. High school teachers, urban teachers, and those from the smallest districts found privacy issues, expense issues, and need for computer-based instruction less worrisome than the middle and elementary teachers. In general, elementary teachers found the three issues to be more worrisome than middle and high school teachers.

Inconsistencies

The Horizon Reports (Freeman et al., 2017; Johnson et al., 2013; Johnson et al., 2014) gave the impression that radical changes in approaches to instruction, including adoption of learning analytics, would evolve over the decade of 2010. Based on a sample of K-12 teachers in North Carolina, the results of the current study do not support the prediction of the Horizon

Report. While many aspects of data use and learning analytics are evolving, the pace of the innovation does not mirror the Horizon prediction. Review of survey results provided some explanation but raised many questions. While teacher awareness of the concept of learning analytics, in general was barely over 50%, many teachers did indicate that they use selected aspects of learning analytics in order to provide a more individualized level of instruction. Usage of some of the typical strategies associated with use of learning analytics in K-12 classrooms does occur but many of the common strategies were seldom used. Resources, in general, would need to be improved especially in training, leadership, and time for pursuing innovation. Attitude, however, was very positive regarding teachers' interest in learning more about use of learning analytics in their classrooms. Several noteworthy areas of inconsistency, or gaps between the literature review and survey results, include the following: lack of empirical research on usage of learning analytics, use of big data as a summative strategy, and teacher training in both technology and data use.

Lack of Empirical Studies. Overall the literature that focuses on usage of leaning analytics in K-12 classrooms is disjointed and scanty. Finding results of empirical investigations specifically related to use of learning analytics in K-12 classrooms are few and far between. Even less available are articles where teacher opinions are heard. Considerably more studies have been published regarding usage of learning analytics in higher education. While cognitive development of students is a likely factor in the divide between K-12 and higher education, often the "publish or perish" mindset amongst those in tenure-track positions in higher education results in greater scholarly productivity. A common practice associated with scholarship in higher education is production of publishable studies of innovation in the classroom. While some

K-12 teachers are encouraged to publish personal case studies from their classrooms, scholarly venues for dissemination that lack generalizability are often limited.

Big Data. Big data are used in educational settings as a summative strategy, one where punitive outcomes among stakeholders are a source of fear. Summative results are often produced to provide documentation for accountability purposes. Once the requirements are met, seldom is time available to go beyond. Learning analytics, at the micro-level in the classroom, is much more associated with formative strategies and the personalization of instruction. Classroom teachers are being asked to do more and more each year in regard to documentation and tracking of their students. Again, once the requirements are met, seldom is more time available to go beyond. The disconnect is in giving teachers the resources they need to be innovative and to break the mold of one size fits all in education. Time, including resources, support personnel, and training, is a huge factor in regard to innovation.

Teacher Preparation. Preparation and continuing education for teachers is another area of concern. If teachers graduate with bachelors' degrees at approximately age 22 and continue their careers until approximately age 62, their knowledge base, not only of their subject expertise but also their knowledge of innovative teaching strategies, spans 40 years. School districts and professional organizations have an obligation to continually expand the expertise of classroom teachers. Institutions of higher education have a similar obligation to continually update classes for teacher trainees and for teachers wishing to add certifications. Technology advances are so rapid that even the best teachers can easily fall behind. According to Mandinach and Gummer (2013), "although some professional development opportunities exist for current educators, few formal courses and opportunities for data literacy development in schools of education have been developed and implemented" (p. 1).

Implications

Current Practice

At one point, a primary function of a school was to provide a safe environment in which students could learn. Much of the energy used for creating schools and curricula adhered to the quote that Spock, of Star Trek fame, made famous: "The needs of the many outweigh the needs of the few" (Meyer, 1982). With the growing discipline of data analytics and the application of learning analytics in education, the potential to individualize learning for every student exists (Ferguson, 2012). A student's foundation of knowledge and skills can be assessed, and predictions can be made to enable each student to have learning targets and benchmarks that accurately reflect how and at what pace the student learns (Ferguson, 2012). Curricula no longer need to be cobbled together in a piecewise fashion to ensure that only the needs of most students are met. Implications for practice are abundant. Four areas seem of particular relevance to usage of learning analytics in current practice: leadership with related implications for funding, preparation for unknown needs and situations like the pandemic of 2020, development of technical skills and retention of teachers, and infrastructure to guide the advancement of underlying technologies.

Leadership and funding. The findings of the current study imply that learning analytics in K-12 is pursued in a piecemeal manner with uncertain resources and goals to facilitate the innovation. Educational institutions must evaluate the potential of learning analytics and develop a long-term approach. While teachers are typically enabled to make some modifications to the standard curriculum, workloads and personal lives typically take priority over extra efforts to implement and fund new strategies. Educational literature suggests that a strong leader is needed to implement widespread change and innovation in educational settings. Plus, funding is needed to adjust the workloads of school personnel in making significant changes.

Adaptability in times of uncertainty. Educational technology has vast potential to provide resources adaptable to unknown and unpredictable situations. Learning analytics can provide a pathway to serving varied populations of students when the consistency of resources across students becomes disjointed. The education sector was left unprepared by the 2020 pandemic when instruction for all ages was moved to a distance-learning format. Had strategies been in place to provide the computer resources across all communities and to adapt curricula to distance formats, much of the stress and uncertainty among all stakeholders might have been less overwhelming.

Development of technical skills and retention of teachers. Jobs in the technology sector are often listed as under-served by applicants with needed skills. Once teachers are trained to apply advanced technologies in their day-to-day teaching, will they become more appealing to the private sector? Will educational institutions be able to compete with salaries, benefits, and working conditions to retain teachers highly skilled in data use?

Underlying infrastructure. While each learner may be supplied with identical information and use a shared vocabulary when discussing a topic, deep understanding of the issue can be vastly different (Mor, Ferguson, & Wasson, 2015). Awareness of the software or analytical framework that analysts use to supply answers is essential. In use of analytics, the prevalent approach to data analysis does not permit fluid outcomes from putting the same data into the system with the expectation of getting the same result every time. Analytic systems can differ according to who and how they were constructed. Every analyst and practitioner is going to construct their analytical framework according to their personal experience and ability, much like that of a learner's own framework in Piaget's original theory of cognitive constructivism (Le Moigne, 2011).

Further Research

Future research should hone in on what it would take to make learning analytics more viable in public education. Attitudes are great! Wherewithal is lacking. If, in fact, use of data to guide instruction is worthy, then more understanding of how to integrate the process into daily activity within classrooms is needed. An ideal approach to further research would be an evaluation of the outcomes of a large-scale, school-wide pilot use of learning analytics, with needed resources and personnel available. Starting with needs assessment and goal setting to implementation and finally evaluation research would provide a model for K-12 use of learning analytics to improve and individualize the instruction of each student.

Research to answer questions like the following is essential:

- What level of training is needed to prepare teachers for transition from the one-size fits all to the individualized approach and to the appropriate understanding of measurement error in decision-making?
- What happens to the retention of teachers with significant technical skills?
- Have the school systems with greater implementation of learning analytics fared better during the 2020 pandemic?
- Has the use of online learning required by many schools, along with associated technologies, changed the impressions of technology and data-use among K-12 teachers?
- How would results from a qualitative or mixed-methods study compare to a quantitative approach?

- Where is the disconnect between positive attitudes and frustrating implementation?
- What factors are dissuading teachers from adopting learning analytics?
- Did accommodating learning during the 2020 pandemic have long-term effects on public education policy and delivery via learning analytic platforms?

Summary

Survey results add to the conclusions found in many of the themes in the literature review. A number of authors pointed out that the rationale makes sense but the implementation is much too cumbersome. Furthermore, much of the empirical work on learning analytics does not include K-12 education but focuses on higher education. While the literature clearly defines learning analytics, the general awareness and usage among the respondents was a disconnected approach to strategies and uses that might have appealed to them or the leadership of their schools. Many respondents indicated that resources for use of data in the classroom were available and attitudes about skill and interest were positive, yet no cohesive strategy emerged. The results do not support the 2013 Horizon Report that learning analytics would be widely adopted within three years.

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Appendix

Survey Introduction and Items

Learning Analytics 4.0

Welcome to the Learning Analytics Survey

As a doctoral candidate in the College of Education at Appalachian State University, I am administering a survey to collect opinions concerning the status of learning analytics in classrooms. Learning analytics is an adaptation of business analytics used by corporations to predict consumer trends and demand. In an educational context, learning analytics refers to use of data to help educators make instructional decisions and predict future performance and outcomes of students.
Learning analytics has been a consideration in public education for nearly a decade. Your opinions about learning analytics within the context of classrooms will inform stakeholders of how those on the front lines of implementing this innovative are using data to advance learning. The information you provide will help in the development of better ways to provide course content, recommend curriculum strategies, and establish educational support and funding for innovation.
Certain criteria for participation will be assessed at the beginning of the survey. The survey should take no longer than 10 minutes to complete. Participation is completely anonymous and voluntary; no identifying information will be collected. Results will be presented in aggregate form.
You can access the survey through the link below:
Instructions for Responding to the Survey: Respond to all items to the best of your knowledge and experience. If you are unsure of your response to an item, use the “No Opinion” option—do not skip or omit items. When progressing through the survey items, use ONLY the arrows at the bottom of your screen—use the right arrow to move FORWARD and the left arrow to move BACKWARDS. The survey will automatically store your responses. You can exit the survey and return by using the same survey link.

Start of Block: Screening

Q1.1 Do you currently hold a valid teaching license issued by the North Carolina Department of Public Instruction (NCDPI)?

○ Yes (1)

○ No (2)

End of Block: Screening

Start of Block: Descriptive Information

Q2.1 Are you currently employed at a K-12 school in North Carolina?

○ Yes (1)

○ No (2)

Q2.2 Which best describes your school?

○ Elementary School (1)

○ Middle School (2)

○ High School (3)

Q2.3 Which best describes your district?

○ Urban (1)

○ Rural (2)

○ Suburban (3)

Q2.4 How many students does your district serve?

○ <5000 (2)

○ 5001-10000 (3)

○ >10000 (5)

Q2.5 Does your teaching responsibility typically include one or more classes with high stakes (e.g., EOG test) outcomes?

○ Always (1)

○ Usually (2)

○ Seldom (3)

○ Never (4)

Q2.6 How many years has it been since you earned hours from an accredited college or university?

- ○ 0 to 5 years (1)
- ○ 6 to 10 years (2)
- ○ 11 to 15 years (3)
- ○ 16 to 20 years (4)
- ○ 21 to 25 years (5)
- ○ 26 years or more (6)

Q2.7 What degrees and certifications do you have? Click all that apply.

- ▢ Bachelors (1)
- ▢ Masters (2)
- ▢ Doctorate (3)
- ▢ Educational Specialist (4)
- ▢ Add-on Certification (5)
- ▢ National Board Certification (6)

End of Block: Descriptive Information

Start of Block: Research Question 1: Awareness

Q3.1 I am aware of an educational trend referred to as Learning Analytics (see survey directions for definition).

- ○ From within my district (1)
- ○ From outside of my district (2)
- ○ From both (3)
- ○ From neither (4)

Q3.2 I have heard about using Learning Analytics in my classroom through information provided at the **district** level.

- ○ Strongly agree (1)
- ○ Somewhat agree (2)
- ○ Somewhat disagree (3)
- ○ Strongly disagree (4)

Q3.3 I have heard about using Learning Analytics in my classroom through information provided at the **school** level.

- ○ Strongly agree (1)
- ○ Somewhat agree (2)
- ○ Somewhat disagree (3)
- ○ Strongly disagree (4)

Q3.4 I have heard about using Learning Analytics in my classroom through information provided by **professional opportunities** like journals, professional development, memberships in professional organizations, and/or conferences.

- Strongly agree (1)
- Somewhat agree (2)
- Somewhat disagree (3)
- Strongly disagree (4)

Q3.5 I have heard about using Learning Analytics in my classroom through information provided by **educational opportunities** like college classes.

- Strongly agree (1)
- Somewhat agree (2)
- Somewhat disagree (3)
- Strongly disagree (4)

Q3.6 Beyond the typical use of test scores, grades, enrollment, and behavioral data, I have become aware of an educational trend where data about individual students are used to make **formative** decisions about student achievement.

- ○ From within my district (1)
- ○ From outside of my district (2)
- ○ From both (3)
- ○ From neither (4)

Q3.7 Beyond the typical use of test scores, grades, enrollment, and behavioral data, I am aware of an educational trend where data about individual students are used to make **summative** decisions about student achievement.

- ○ From within my district (1)
- ○ From outside of my district (2)
- ○ From both (3)
- ○ From neither (4)

End of Block: Research Question 1: Awareness

Start of Block: Research Question 2: Usage

Q4.1 I use learning analytics in my daily practice.

- ○ Strongly agree (1)
- ○ Somewhat agree (2)
- ○ Somewhat disagree (3)
- ○ Strongly disagree (4)

Q4.2 How do you use learning analytics? Click all that apply.

- ▢ Formative Assessments (1)
- ▢ Summative Assessments (2)
- ▢ Descriptive Assessments (3)
- ▢ Descriptive Data (4)
- ▢ Making Predictions (5)
- ▢ Drawing Conclusions (6)
- ▢ Comparing/Contrasting (7)
- ▢ Setting Goals and Objectives (8)
- ▢ Differentiating Instruction (9)
- ▢ Self-evaluation (10)

Q4.3 What learning analytics strategies do you use? Click all that apply.

- [ ] Personalize Learning Experiences (1)
- [ ] Motivate Reaching Goals (2)
- [ ] Monitor Progress (3)
- [ ] Conduct Self-Assessments (4)
- [ ] Modify Content According to Interest (5)
- [ ] Modify Content According to Difficulty (6)
- [ ] Modify Negative Habits (7)
- [ ] Identify At-Risk Students (8)
- [ ] Computer Score Essays (9)
- [ ] Produce Time Management Aid (10)

Q4.4 Approximately, how many members of your school's faculty use learning analytics?

- ○ 100 % (1)
- ○ 75% to 99% (2)
- ○ 50% to 74% (3)
- ○ 25% to 49% (4)
- ○ 0% to 24% (5)
- ○ Unsure (6)

Q4.5 Estimate how often you or other members of your faculty use learning analytics?

- ○ Daily (1)
- ○ Weekly (2)
- ○ Monthly (3)
- ○ A Few Times a Semester (4)
- ○ A Few Times a Year (5)
- ○ Never (6)
- ○ Unsure (7)

Q4.6 Who **has access** to learning analytics at your school or district? Click all that apply.

- ☐ Teachers (1)
- ☐ Counselors (2)
- ☐ Licensed Support Staff (3)
- ☐ Tech Support (4)
- ☐ School Administrators (5)
- ☐ District Administrators (6)
- ☐ Students (7)
- ☐ Parents (8)
- ☐ Unsure (9)

Q4.7 Who **uses** learning analytics at your school or district? Click all that apply.

- ☐ Teachers (1)
- ☐ Counselors (2)
- ☐ Licensed Support Staff (3)
- ☐ Tech Support (4)
- ☐ School Administrators (5)
- ☐ District Administrators (6)
- ☐ Students (7)
- ☐ Parents (8)
- ☐ Unsure (9)

End of Block: Research Question 2: Usage

Start of Block: Research Question 3: Resources

Q5.1 My district has an employee position, assigned to work directly with teachers, **to consult on instructional design**.

- ○ Yes (45)
- ○ No (46)
- ○ Unsure (47)

Q5.2 My district has an employee position, assigned to work directly with teachers, to consult on **technical issues with computers in the classroom**.

- ◯ Yes (1)
- ◯ No (2)
- ◯ Unsure (3)

Q5.3 My district has an employee position assigned t**o manage student databases.**

- ◯ Yes (1)
- ◯ No (2)
- ◯ Unsure (3)

Q5.4 My district has professional development training for teachers **on innovative classroom strategies**.

- ◯ Yes (1)
- ◯ No (2)
- ◯ Unsure (3)

Q5.5 My district has professional development training for teachers **on the use of learning analytics**.

- Yes (1)
- No (2)
- Unsure (3)

Q5.6 My district has provided **out-of-district training** (e.g., professional conferences and/or workshops) for teachers on the use of learning analytics.

- Yes (1)
- No (2)
- Unsure (3)

Q5.7 My district has provided **reduced teaching loads** for teachers to develop strategies for using learning analytics.

- Yes (1)
- No (2)
- Unsure (3)

Q5.8 My district has established **committees** (or other means of collaboration such as social media) for teachers to interact concerning their use of learning analytics in the classroom.

- Yes (1)
- No (2)
- Unsure (3)

Q5.9 My district has established **forums** where classroom teachers can have a voice in the adoption of innovative teaching strategies.

- Yes (1)
- No (2)
- Unsure (3)

End of Block: Research Question 3: Resources

Start of Block: Research Question 4: Attitude

Q6.1 I find online instructional materials that include individualized student feedback, both formative and/or summative, to be very useful.

- Strongly agree (1)
- Somewhat agree (2)
- Somewhat disagree (3)
- Strongly disagree (4)

Q6.2 I think that I have the background and ability, with computer technology, to benefit from training about use of learning analytics in the classroom.

- Strongly agree (1)
- Somewhat agree (2)
- Somewhat disagree (3)
- Strongly disagree (4)

Q6.3 I would like to know more about how to incorporate learning analytics into my classroom instructional strategies.

- Strongly agree (1)
- Somewhat agree (2)
- Somewhat disagree (3)
- Strongly disagree (4)

Q6.4 I think that learning analytics has too much potential to violate privacy to be useful in the classroom.

- ○ Strongly agree (1)
- ○ Somewhat agree (2)
- ○ Somewhat disagree (3)
- ○ Strongly disagree (4)

Q6.5 I think that learning analytics is too expensive for individual teacher use.

- ○ Strongly agree (1)
- ○ Somewhat agree (2)
- ○ Somewhat disagree (3)
- ○ Strongly disagree (4)

Q6.6 I think that learning analytics will not be viable until all instruction is computer based.

- ○ Strongly agree (1)
- ○ Somewhat agree (2)
- ○ Somewhat disagree (3)
- ○ Strongly disagree (4)

Q6.7 I think that learning analytics will be popular with districts that have the resources to computerize their instructional programs.

- Strongly agree (1)
- Somewhat agree (2)
- Somewhat disagree (3)
- Strongly disagree (4)

Q6.8 I think that learning analytics have great potential for use in the classroom.

- Strongly agree (1)
- Somewhat agree (2)
- Somewhat disagree (3)
- Strongly disagree (4)

Q6.9 I think that learning analytics should be geared toward minimizing paperwork and maximizing face-to-face time with individual students.

- Strongly agree (1)
- Somewhat agree (2)
- Somewhat disagree (3)
- Strongly disagree (4)

End of Block: Research Question 4: Attitude

Vita

Tonia Lea Olson Baldwin was born in Dallas, Texas, to George and Margot Olson. She graduated from The Winston School in Texas in May 1989. She attended the University of North Texas and Richland College before entering Appalachian State University to study Political Science in the fall of 1992. In December 1998 she was awarded the Bachelor of Science degree. After teaching for several years, she began study in 2003 at Appalachian State University towards a Master of Arts Degree. The M.A. was awarded in December 2006. In the summer of 2013, Ms. Olson commenced work towards her Ed. D. in Educational Leadership at Appalachian State University. While working towards her Ed.D., she earned a Graduate Certificate in Business Analytics from Appalachian State University in May 2016.

Ms. Olson is member of the North Carolina Association of Educators and currently teaching for Durham Public Schools. She resides in Durham, NC with her husband and their two dogs.