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The Nature and Extent of Instructors' Use of Learning Analytics in Higher Education to Inform Teaching and Learning

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THE NATURE AND EXTENT OF INSTRUCTORS' USE OF LEARNING ANALYTICS

IN HIGHER EDUCATION TO INFORM TEACHING AND LEARNING

By

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Abstract

The utilization of learning analytics to support teaching and learning has emerged as a newer phenomenon combining instructor-oriented action research, the mining of educational data, and the analyses of statistics and patterns. Learning analytics have documented, quantified and graphically displayed students' interactions, engagement, and performance to gain a more complex understanding of teaching and learning. Researchers and scholars have hailed learning analytics as one of the future game-changers in higher education. This study addressed important questions. How have instructors at institutions of higher learning explored learning analytics to reflect upon their teaching practice—specifically, curriculum, pedagogy, student learning and outcomes? What have been the perceived key challenges to the adoption and implementation of learning analytics by instructors at institutions of higher learning? A reflection on technology integration with an emphasis on the affordances and rhetoric of learning analytics to inform teaching and learning was presented. An exploratory study was undertaken consisting of a two-phased research approach–a dominant-less dominant design, addressing the nature and extent of instructors' use of learning analytics in higher education. The findings failed to substantiate extensive buy-in by instructors; challenges included a lack of time to learn and implement analytics, a culture of resistance, issues with change, and insufficient professional development, training and incentives. When learning analytics were used, it often involved supervisory and pro-active affordances for students.

Keywords: learning analytics, learning management system, prediction, student outcomes, retention, higher education, professional development

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Chapter 1

Introduction to the Study

The topic of this study was the exploration of instructors' usage of learning analytics at institutions of higher learning to inform teaching and learning. Dynamic in nature, the field of learning analytics has celebrated a relatively short life, evolving out of internet-based learning management systems. With the advancement of computer technology, change has characterized the nature of learning in higher education over the past decades, creating promises, challenges and disruptive moments (Bass, 2012; Christensen & Eyring, 2011; Christensen, 2011; Fullan, 2011; Issroff & Scanlon, 2002; Strudler, McKinney, Jones & Quinn, 1999; Strudler & Wetzel, 1999). Learning management systems have proliferated higher education, hosting enhanced course offerings and affording the use of new technological tools assisting teaching practice. Learning has become ubiquitous and complex— offering greater usability as a result of flexibility in course offerings and the accessibility of educational resources (Bichsel, 2013). Higher educational institutions have utilized a variety of approaches for the delivery of courses online. According to Bichsel (2013):

> Institutions take various approaches to delivering e-learning services and technologies. Some manage e-learning services through central IT; others manage e-learning through different or multiple departments. Some institutions provide e-learning services and technologies centrally, and some have a distributed or mixed approach. There are multiple paths for the successful provision of e-learning, and the selection and delivery of e-learning services and technologies depend on factors such as institution size, mission, and the priorities of institutional leaders. (p. 2)

These initiatives have resulted in increased enrollments and revenue as well as an enhancement of the institution's reputation due to a more enriched teaching and learning experience (Bichsel, 2013).

There has been a confluence of trends including, but not limited to, the development, acquisition and integration of new technological tools within learning management systems. These tools, with learning analytics in the forefront, are powerful, collaborative and appealing (Chatti, Dyckhoff, Schroeder, & Thus, 2015; IIyoshi & Kumar, 2016; Resta & Laferriere, 2007). Technology has become widely accepted as an integral component of teaching practice (Fullan, 2011; Mishra & Kohler, 2006; Mishra & Kohler, 2009). Researchers have postulated that technology integration within teaching practices is critical; rich learning experiences are often dependent upon not only course materials but advanced technologies and devices (Koehler & Mishra, 2009; IIyoshi and Kumar, 2016). An emphasis has been placed on the need to collect, share, distribute, cluster, vet, and try new contexts. According to Koehler, Mishra, and Cain (2013), "Teaching with technology is complicated further when the challenges newer technologies present to teachers are considered" (p. 13). With any technological change, challenges have emerged.

Inasmuch as supporting teaching and learning in higher education with technological advances would appear to be routine in our modern society, the utilization of learning analytics has emerged as a newer phenomenon combining instructor-oriented action research, the mining of educational data, and the analyses of statistics and patterns. The increasing usage of educational data and advances in computer technology in higher education have allowed interactions, engagement and behaviors to be documented, quantified and analyzed to gain a

more complex consideration of teaching and learning (Baker & Siemens, 2011; Barneveld, Arnold, & Campbell, 2012; Chatti et al., 2015).

The Advent of Learning Analytics

The field of learning analytics is innovative, relatively young, and dynamic evolving out of internet-based e-learning environments. Learning analytics numerically and graphically document students' online presence, performance and activity within learning management systems. These may be used by instructors to gain a better understanding of students' learning and greater reflection into their own teaching processes. In 1970, the journal dedicated to technology and analytics—*Computers in Biology and Medicine* was published. This journal proved to be revolutionary for its time, as it combined computer applications to the fields of bioscience and medicine. The term academic analytics was coined by WebCT (now known as Blackboard) in 2005, in the same year as the first data mining workshop— *The 1st International Workshop on Open Source Data Mining* (Chatti et al., 2015). An international journal devoted to the interdisciplinary research on the data mining of student data began publication in 2009—*The Journal of Educational Data Mining* (Baker & and Siemens, 2013). In 2011, the 1st International Conference on Learning Analytics and Knowledge—for the reporting and advancement of research, was conducted in Canada (Larusson & and White, 2014). According to Baker and Siemens (2011), there are three prominent resources for learning analytics: (a) The *Journal of Learning Analytics,* (b) the International Conference on Educational Data Mining, and (c) the Conference on Learning Analytics and Knowledge. In addition to these, research has proliferated literature in numerous fields and professional journals. Learning analytics have continued to gain momentum as researchers and scholars reflect on the affordances and

challenges of tapping into the metrics behind students' activities and engagements in course offerings.

Conceptualization of Learning Analytics

This study focused on the extent and nature of learning analytics usage by instructors in higher education in their practice of teaching. Although the field of learning analytics has a relatively short life—a multitude of terms, definitions and constructs have appeared. For the sake of clarity, three types of learning analytics have been conceptualized into a single term (predictive, academic, and action analytics). According to Barneveld and colleagues (2012), all analytics in higher education have the capacity to work together in unity as a whole—serving the needs of stakeholders on a multiplicity of levels (Figure 1).

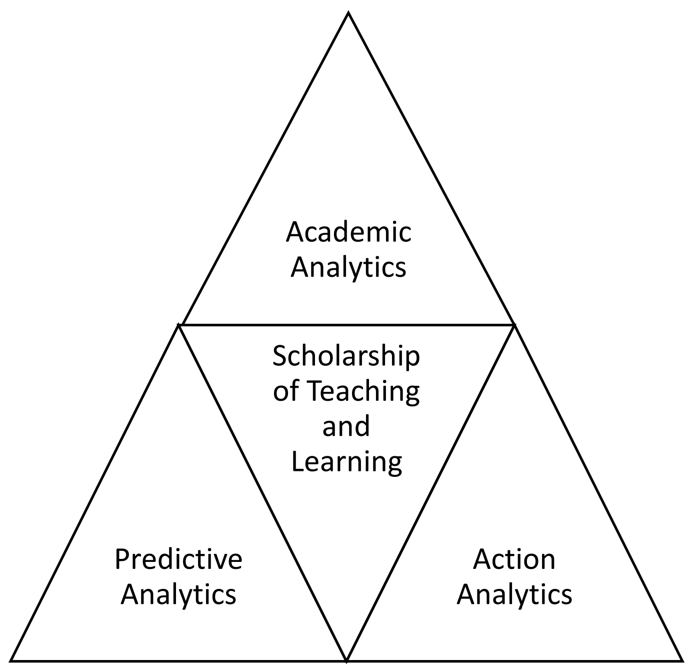

Figure 1. Conceptual framework of learning analytics. This figure illustrates a theoretical framework reflecting on a previous conceptualization by Barnevald et al. (2012).

According to Barnevald and colleagues (2012), the scholarship of teaching and learning serves as a focal point and backbone of learning analytics. Academic, action and predictive analytics have been considered a part of the whole supported through and by the key transformative piece—scholarship of teaching and learning. In this connection, scholarship of teaching and learning has often depended upon various factors including, (a) the sharing of knowledge and experiences, (b) transition and change, and (c) open and accessible professional development opportunities to ensure successful implementation.

Statement of the Problem

There has been an insufficiency of literature on the buy-in, implementation and ongoing usage of learning analytics by instructors in higher education. Learning analytics have been heralded as one of the technologies changing and capable of reshaping the landscape of higher education (Bichsel, 2012; Dahlstrom & Brooks, 2014; Dahlstrom et al., 2014; Educause, 2012; Gasevic, Dawson, & Siemens, 2016; Johnson et al., 2014; Johnson et al., 2016). But, it was not apparent in the literature that studies have been piloted reflecting specifically upon instructors' use, including buy-in, professional development opportunities, knowledge, and integration into their teaching practice. The present research study addressed the gap in literature between the promises presented through research studies on the affordances of learning analytics and actual use by instructors. Siemens (2012) referred to this as the *research and practice gap*, which is well-known in numerous fields and has been evident with learning analytics. Beer and Tickner (2014) also mentioned this as a "… gap between the rhetoric around the virtues of e-learning and the complicated reality of the e-learning lived experience," and referred to it as a movement toward *faddism* (p. 242). Siemens (2012) and Beer and Tickner (2014) contend that learning

analytics may fail to live up to its promise of making a substantial and meaningful impact on teaching and learning. Siemens (2012) suggested,

> The work of researchers often sits in isolation from that of vendors and of end users or practitioners. This gap is challenging as it reflects a broken cycle of communication and interaction between empirical research and how those findings are translated into practice. (p. 2)

Chatti and colleagues (2015) asserted, “Currently many of the systems are data rich, but information poor” (p. 12). According to Johnson et al. (2014), “While interest is considerable, higher education in general has yet to fully embrace these sorts of processes . . . but the potential of using data to improve services, student retention, and student success is clearly evident” (p. 12). So the question has been posited: To what extent do instructors use learning analytics to explore teaching practices and reflect upon students’ learning? Siemens (2012) urged that there must be a buy-in of practitioners to drive the adoption of analytics in education. Johnson et al. (2014) contend that the idea is to “… use data to adapt instruction to individual learner needs in real-time in the same way that Amazon, Netflix, and Google use metrics to tailor recommendations to consumer” (p.38). A second question of importance: Are professional development opportunities afforded to instructors to support their usage of learning analytics in their current teaching practice? These questions helped shape the statement of the problem and review of literature.

According to Dahlstrom, Brooks, and Bichsel (2014), even though instructors have valued the tools within learning management systems as having great potential to aid in student learning, many of them are often underused, referring to this as an *underutilization phenomenon* (p. 11). This discrepancy is believed to be partly contributable to the intricate nature of the data,

complex details of the systems, and the integration process (relating to insufficient professional development and learning opportunities). According to the authors, few instructors have used the more advanced tools found within learning management systems; rarely have instructors used the systems to their maximum capacity.

Upon review of the literature on learning analytics and an inquiry to professionals at Educause, there was a noted lack of data in reference to instructors' usage of learning analytics to inform teaching and learning. Furthermore, it was unclear whether professional development has been afforded to instructors wishing to learn and implement analytics into their practice. According to Dahlstrom (personal communication, September 19, 2016) and in reference to her research on learning analytics and on faculty use of technology, "Most of the literature we came across in our investigation was on efficacy of learning analytics rather than extent of use." Also, relating to the lack of research in reference to instructors' practice, "There is a small section in the *2015 ECAR Faculty Study* about faculty use of and opinions about learning analytics," according to Dahlstrom (personal communication, September 19, 2016). Therefore, the present study addressed this gap in literature by exploring the extent, nature, and use of learning analytics by instructors in higher education to reflect upon teaching and learning.

In reference to the statement of the problem and based upon the review of literature, the following research questions were addressed:

RQ1: How do instructors at institutions of higher learning explore learning analytics to reflect upon their teaching practices, curriculum, or pedagogy?

RQ2: How do instructors at institutions of higher learning explore learning analytics to reflect upon student learning and outcomes?

RQ3: What are the perceived key challenges to the adoption or use of learning analytics by instructors at institutions of higher learning?

Theoretical Foundation

During the last twenty years, theory to support the use of learning analytics has been scarce (Gasevic, Dawson, & Siemens, 2016). Chen (2015) argued, "Despite learning analytics' emphasis on the practical side of measuring, collecting, analyzing and reporting educational data, theory has been an important concern ever since the emergence of the field" (p. 163). Studies have reflected upon learning theories including self-regulated learning, teacher learning, experiential learning, cognitive load theory and schema, activity theory, sociocritical perspective, the dissemination of innovation, and concerns-based adoption models as exerting theoretical importance (Ashe & Bibi, 2011; Bass, 2012; Borthwick & Pierson, 2008; Chen, 2015; Gasevic et al., 2016; Issroff & Scanlon, 2002; Issroff & Scanlon, 2002b; Kuuti, 1996; Slade & Prinsloo, 2014).

While it is uncertain whether instructors have reflected upon learning analytics in learning management systems to inform their own teaching practices in today's educational arena, issues of teacher change have been central to discussions on technology implementation (Ertmer & Ottenbreit-Leftwich, 2010). Utilization of learning analytics have been thoughtfully explored through arguments for Technology Pedagogical Content Knowledge, more popularly known as TPACK (Koehler, Mishra, & Cain, 2013; Mishra & Kohler, 2006; Mishra, Koehler, & Kereluik, 2009).

The catalyst for change. Ertmer and Ottenbreit-Leftwich (2010) argued that change is often needed in belief systems, pedagogy, content knowledge, instructional practices, and resources when implementing technology. Fullan (2011) referred to the *stratosphere* as the intersection of

technology, pedagogy, and change theory. Change has been hampered due to insufficient knowledge, belief systems, low self-efficacy, a lack of teacher-centered focus, and institutional pressures to conform. According to scholars, small changes tend to impact teacher change more efficiently than more complex endeavors (Ertmer & Ottenbreit-Leftwich, 2010; Bain & McNaught, 2006). According to Fullan (2011):

> Change will become more enjoyable when it proffers experiences that are engaging, precise, and specific; high yield (good benefit relative to effort); higher order (stretching humans in creativity, problem solving, and innovation); and collaborative for individual and collective benefit. (p. 3)

MacFadyen and Dawson (2012) recognized the resistance of institutions to change or evolve over time. Ertmer and Ottenbreit-Leftwich (2010) suggested that numbers alone are not enough to affect change, proposing, "… greater attention is needed to the accessibility and presentation of analytics processes and findings so that learning analytics discoveries also have the capacity to surprise and compel, and thus motivate behavioural change" (p. 161). Often instructors have not been convinced that change is needed because the field of educational technology lacks the empirical proof that technology integration leads to increased achievement (Borthwick & Pierson, 2008). Kotter (1995; 2016) delineated eight steps in efficiently implementing change. Although this construct originated from a business paradigm, relevance may be rendered to the field of education (see Figure 2).

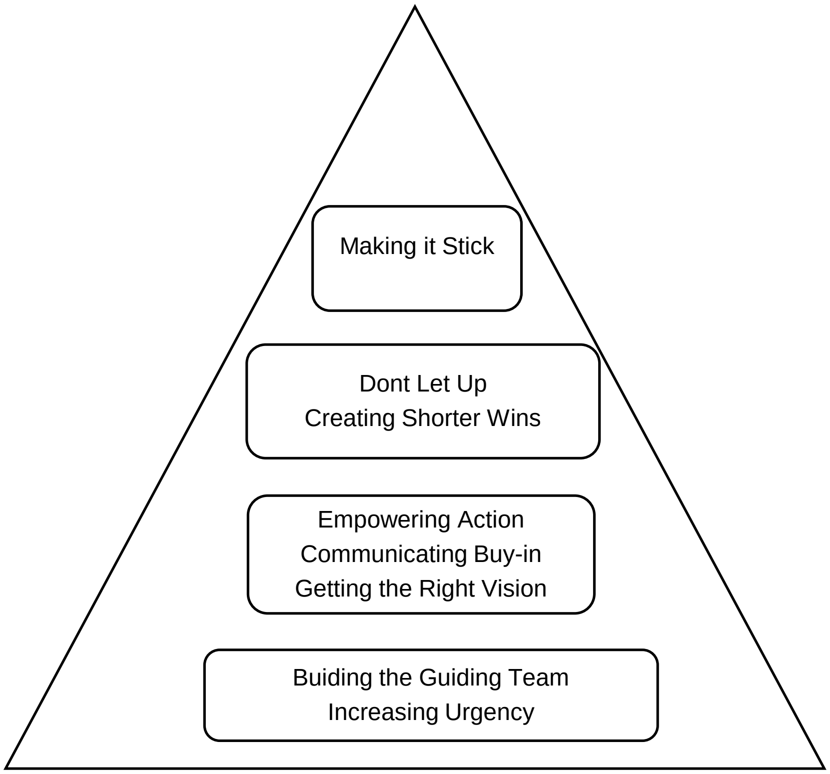

Figure 2. Kotter's eight steps in successfully implementing change. Kotter (1995; 2016) distinguished eight steps in successfully implementing change.

According to Kotter (1995; 2016), the primary step in implementing change is one that instills a substantial sense of urgency—necessitating high levels of motivation. Without motivation, the effort often dissipates. To implement change, a careful examination of the current situation must be explored to allow for the identification of potential threats and opportunities. Urgency dictates that the information should be communicated broadly, dramatically, and in a timely manner. Mishra et al. (2009) added that "Throughout history new technologies have been hailed as the next, best thing" and often instructors and institutions have chased the latest and greatest innovations (p. 48). With the case of learning analytics, it has been heralded as one of the major future game-changers in higher education by scholars and researchers (Bichsel, 2012; Dahlstrom & Brooks, 2014; Dahlstrom et al., 2014; Educause, 2012;

Gasevic, Dawson, & Siemens, 2016; Johnson et al., 2014; Johnson et al., 2016). Although there is considerable enthusiasm, unless it is coupled with motivation, change may not occur.

Although urgency has been clearly demonstrated due to the plethora of literature on learning analytics, the extent of buy-in by instructors and their particular use patterns have yet to be explored. According to Kotter (1995), transformation has required the aggressive cooperation of many (p. 2). Certainly, this would include the aggressive participation by instructors; to date, this does not appear to have been appropriately assessed.

It is essential to recognize that scrutiny of Kotter's change model has been illuminated by Appelbaum, Habashy, Malo, and Shafiq (2012), noting that Kotter often cited his own work while rarely acknowledging other studies as references. They added that the popularity of Kotter's change theory appeared to resonate from his straightforward and practical format rather than from scientific preponderance of evidence. In light of Kotter's change model, the present study, was designed to establish whether instructors' buy-in of learning analytics has been aggressive, widespread and substantial. Mishra and Koehler (2006) contend that teachers have often exhibited a fear of change and lack the time required to learn and implement new technologies. Conducting a study at the University of British Columbia, on the use of discussion boards to determine disengaged students, MacFadyen and Dawson (2010) discovered:

> The e-learning analytics data generated in this case study clearly demonstrate that some substantial changes are needed in order to better facilitate adoption and integration of learning technologies into daily curricular activities and support the ethos of student success to which the institution aspires. Interestingly, this mismatch between opportunity and implementation may be more widespread than enthusiastic analytics literature suggests. (p. 159)

When adopting and implementing technology, challenges have abounded. Some have referred to the initial increased urgency in the beginning as a *hype cycle* where successes of the technology (*fads*) have been tempered by reported failures (Beer & Tickner, 2014). Scholars have recognized that some technologies (such as learning analytics) may be classified as *disruptive innovations* (Bass, 2012; Christensen, 2011). MacFadyen and Dawson (2012) contend that learning analytics, having little motivating power and that "Simple availability of new knowledge made available through e-learning analytics, has, however, failed to influence institutional planning in this regard, and has failed to inform development of a strategic vision for learning technology at this institution" (p. 159). According to Mishra et al. (2009), educational revolutions in history have often reflected unrealized visions of change. This unrealized vision was reflected in Fullan's (2011) depiction of the distractibility of some technologies,

> Stratosphere is about opening our eyes to both the dark side of technology and to its virtually unlimited enlightenment side—no powerful tool is ever neutral in its use. In our education reform work, we even have a category, 'beware of distractors'—factors and forces that divert people from maintaining focus on core priorities. Humankind is easily distracted, and all the more so when peers are egging one on. (p. 7)

Romero-Zaldivar, Pardo, Burgos, and Kloos (2012) have discussed forces that prevented successful implementation, including (a) complex interactions of key stakeholders, (b) expanding communication technology, (c) and the cost of a rich comprehensive learning environment. In light of issues of instructors' change and central to the discussion on the implementation of learning analytics, a reflection on TPACK was explored.

Technology, pedagogy, and content knowledge. Calling for an urgency for theoretical vision to serve as a backbone for technology use, Selfe (1990), a pioneer in computer technology implementation, urged, "Until we share some theoretical vision of this topic, we will never glimpse the larger picture that could give our everyday classroom efforts direction and meaning" (p. 119). Mishra and Koehler (2006) building upon the writings of Selfe, urged, "Developing theory for educational technology is difficult because it requires a detailed understanding of complex relationships that are contextually bound" (p. 1018). They argued that the attentive implementation of technology required the execution of a multifaceted and dynamic form of knowledge that is referred to as Technological Pedagogical Content Knowledge (TPACK). TPACK has a robust interchange of multifarious roles with the three main components of learning—content, pedagogy, and technology. They reasoned that the TPACK model offers relevance at various levels including theoretical, pedagogical, and methodological (Figure 3) (Koehler, Mishra, & Cain, 2013).

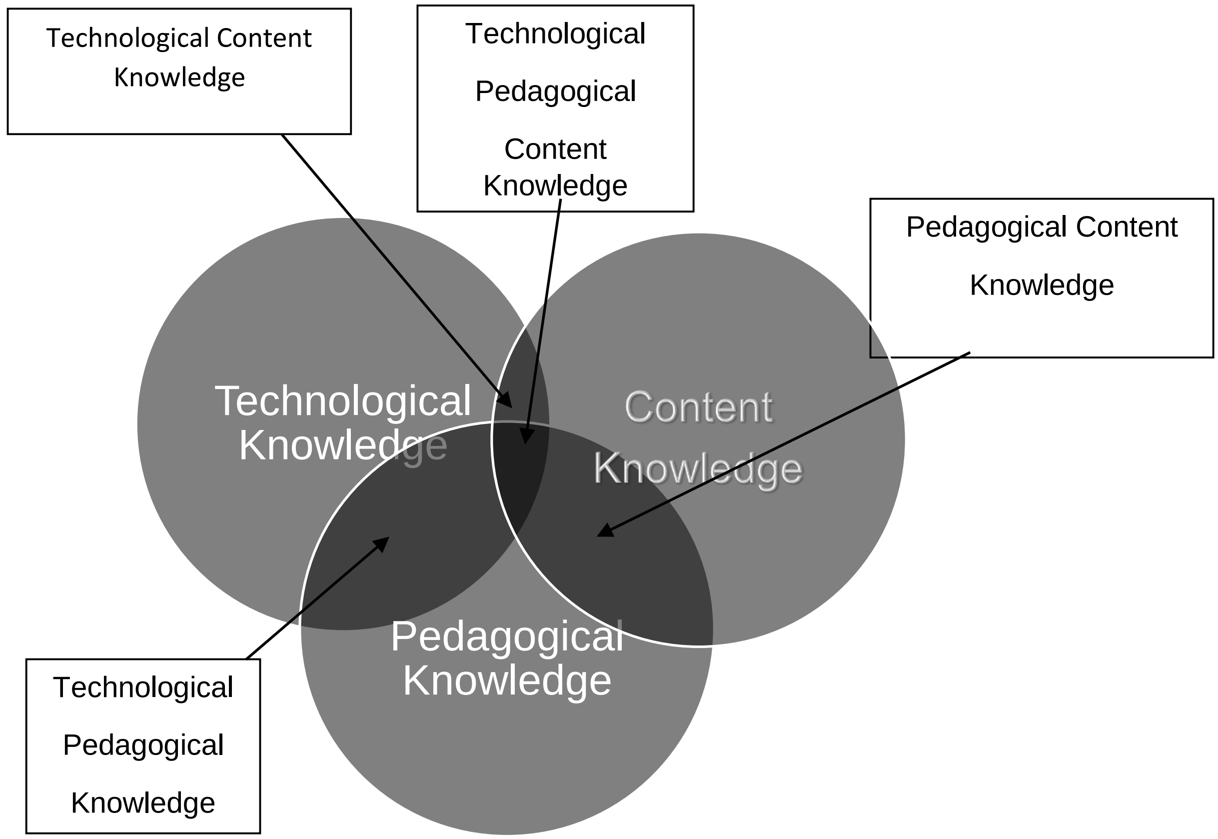

Figure 3. Technological Pedagogical Content Knowledge. Mishra and Koehler's (2006) interconnection of three main components of learning: content, pedagogy and technology.

According to Mishra and Koehler (2006), the three circles (fields) including content, pedagogy, and technology interconnect—leading to the addition of four additional types of interrelated knowledge (see Figure 3). A delineation of the delineation of knowledges are portrayed in Table 1.

Table 1

Mishra and Koehler's Delineation of TPACK

Type of knowledge	What this knowledge entails
Content knowledge	Knowledge about the subject matter
Pedagogical knowledge	Knowledge about teaching and learning
Pedagogical content knowledge	Knowledge of teaching practices
Technology knowledge	Knowledge about educational technologies
Technological content knowledge	Knowledge of reciprocity of technology and content
Technological pedagogical knowledge	Knowledge of the reciprocity of technology and the subject matter
Technological pedagogical content knowledge	An advancing, emerging form of knowledge incorporating content, pedagogy, and technology; constructivist methods incorporating technology; use of technology to rectify issues; development of new epistemologies

According to Mishra and Koehler (2006), a change in any one of the three main knowledge areas (technology, content, or pedagogy) results in changes or compensations to the others. Therefore, one of the central ideas behind TPACK is the integral nature of change theory popularized by Kotter (1996). Accordingly, any new technology, such as learning analytics, has the potential of evoking change in teaching practice–specifically in content and pedagogy. A central premise is

that whenever change occurs, instructors must bring about equilibrium amongst all three elements.

Mishra and Koehler (2006) and Koehler and colleagues (2013) urged a deeper understanding of technology through training, as teaching with technology has been difficult to do well. Technology has been in a constant state of evolution; some technologies may be appropriate for enhanced learning while others have not afforded the same privileges. Emphasis placed on *what and how* have encouraged experimentation through trial and error. The TPACK framework has gleaned its robustness from the complex system of interconnected elements of the three fields; overemphasis on technology has been viewed as being counterproductive. Merely knowing how to use technology has not provided proof that it actually works as intended (Ertmer & Ottenbreit-Leftwich, 2010; Fullan, 2011; Karaman, 2012; Koehler et al., 2013; Mishra & Koehler, 2006). Researchers and scholars have suggested that using technology as an add-on has not been productive; technology has been and should be considered a part of a whole (Mishra, Koehler, & Kereluik, 2009; Strudler et al., 1999). Therefore, effective integration has been achieved when instructors were able to select and implement technology that not only provided content in a timely manner, but allowed for the analysis and synthesis of information to reflect upon teaching practice.

Observations through a theoretical lens ensure guidance and the helpful sense-making of behavior. Theoretical constructs have occupied a pivotal role in the guidance of questions that may be posed, research methods chosen, collection of data, analysis, and recommendations that have been rendered (Mishra & Koehler, 2006). TPACK has provided a directed and calculable approach to teaching practices with learning technologies as well as providing an analytic framework for reviewing the growth and expansion of instructor’s knowledge about learning

technologies. TPACK has enabled instructors to make sense of a complex construct that has existed when instructors have applied technology to teaching and learning of a subject. The TPACK approach has illuminated key criteria that have guided successful integration in a methodologically rich and grounded manner. According to Mishra and Koehler (2006), "The TPACK framework can be used to design pedagogical strategies and an analytic lens to study changes in educators' knowledge about successful teaching with technology" (p. 1046). Consequently, the TPACK framework has accented the crucial role of instructors as designers of their own technology-rich environments, forged upon sound teaching practices that have remained steadfast through changes in technologies, content, and/or pedagogy.

No one theory has been all encompassing and tells the *complete story*; the TPACK framework, has not been without exception (Mishra et al., 2009). Karaman (2012) postulated that TPACK has not been free of criticism. Complaints have arisen from its purported complications, time-consuming design, difficulties in implementation and problematic analyses and interpretations. Karaman (2012) also noted that TPACK has been referred to as more of a theoretical argument rather than a practical one, with "…nothing more than an invented construct to enhance the professional status of teacher educators" (p. 59).

Purpose of the Study

Gaining a better understanding of the nature and extent of instructors' buy-in, implementation and usage of learning analytics in higher education has been the primary purpose of this research study. Beyond this, the scope of the study was to assess any potential challenges to buy-in and implementation of learning analytics. The instruments were designed to gauge the extent and nature of learning analytics practices and to provide descriptive analyses of professional demographics, including years of service, ranking, and type of higher educational

institution. The objective was to tap into the instructors' lived experiences including technology use, research, scholarship, and professional development. Personal and psychological attributes such as motivations, dispositions, satisfactions, needs, expectations and attitude were explored through the use of open-ended questions. Extending the literature with data and information on the actual teaching practices of instructors in reference to their use of learning analytics was an intent of the study, providing practitioners and institutions of higher learning with data that could be utilized to assist all major stakeholders. Therefore, the rationales behind this study have encompassed:

- gaining a better understanding of the affordances and rhetoric of learning analytics in higher education;
- examining the buy-in, implementation and nature of instructor's usage of learning analytics;
- an analysis of learning analytics usage by experts in higher education; and
- supplementing the present body of literature on learning analytics with the added realm of lived instructors' experiences.

In unison, these have the opportunity to improve academia's understanding and knowledge of current learning analytics adoption, integration, and ongoing utilization.

Definitions of Key Terms

The following key terms were used in the scope of this study. These concepts were interpreted by the definitions and terminology listed.

Instructors: This term included those that teach both adjunct and full-time at institutions of higher learning, including colleges, universities, online institutions and graduate schools.

Instructors were used synonymously with faculty, professors, practitioners, educators and teachers.

Learning analytics: According to *Educause's Analytics in Higher Education Report* (Bichsel, 2012b) learning analytics were defined as "… the use of data, statistical analysis, and explanatory and predictive models to gain insights and act on complex issues" (p. 6). Learning analytics were used synonymously with the terms *academic analytics*, coined by WebCT in 2005 (Chatti et al., 2015), and *course analytics* as named by Canvas (2016) to denote their statistics on students' performance and usage (embedded in their respective platforms). Learning analytics were used interchangeably in this study with *data-driven decision making* and *data mining*.

Learning management system: E-learning initiatives have been accomplished through the use of platforms or centralized web-based learning systems–often referred to as learning management systems. These systems have been widely used by institutions of higher learning and designed to host courses, assignments, syllabi, assessments, discussions, and other tools of learning. The literature often cites these learning management systems as virtual learning environments, Webcampus, WebCT, Canvas, Moodle and D2L (Desire to Learn), etc. In more recent years, learning management systems have been provided through book companies and other proprietary vendors.

Professional development: For the purpose of this study, professional development has been referred to as courses, workshops and online resources offered in higher education that have utilized materials, computers, and communication to teach and inform instructors on the discovery of new information and technologies. An affordance of professional development has been increased digital fluency, maximized through the willingness of instructors to embrace new

concepts, ideas and technologies. Professional development was used synonymously with training, workshops, classes and courses providing education and skills acquisition to instructors.

Student outcomes: Student learning outcomes have been referred to as the clearly articulated expectations of knowledge, skills, attitudes, and competencies that learners have been attained through educational pursuits (National Institute of Learning Outcomes, 2016).

Technology: The term *technology*, has been associated with tools and resources created and developed specifically for the educational sector that have promoted learning and improved performance through computerized, digital, technological and communication processes (Mishra et al., 2009). This concept has been used synonymously with educational and instructional technologies. The goal of technology has been the production of desired results while offering both affordances and constraints (Johnson et al., 2014; AACTE Committee on Innovation and Technology, 2008).

Summary

Chapter 1 provided an introduction to learning analytics, the current status of research and theoretical implications. The introduction described the nature and purpose of the study while the remainder of the chapter reflected on the definition of terms, the significance, and justification for this study.

Chapter 2

Review of Literature and Research Questions

The focus of this study was to explore the extent and nature of learning analytics use among college and university instructors, reflecting upon teaching practices. This chapter included a review of the literature with emphasis on (a) technology integration, (b) professional development, (c) case studies of learning analytics initiatives targeting retention and course outcomes, and (d) the rhetoric involving concerns, barriers, and challenges. The review of literature was centered around the following research questions:

RQ1: How do instructors at institutions of higher learning explore learning analytics to reflect upon their teaching practices, curriculum, or pedagogy?

RQ2: How do instructors at institutions of higher learning explore learning analytics to reflect upon student learning and outcomes?

RQ3: What are the perceived key challenges to the adoption or use of learning analytics by instructors at institutions of higher learning?

Learning Analytics

The review of literature on learning analytics produced a flurry of definitions, all denoting a multitude of purposes, affordances, and challenges. In the discourses, a mindfulness of how learning analytics, pedagogy and content have interconnected to impact student learning outcomes was evident. Many of the definitions and characteristics of learning analytics have been pieced together to form a multi-faceted construct. A Department of Education report on educational data mining and learning analytics (Bienkowski, Feng, & Means, 2012) stressed the importance of "…human tailoring of responses, such as through adapting instruction content, intervening with at-risk students and providing feedback" (p. 13). Dietz-Uhler and Horn (2013)

referred to the affordance of learning analytics in terms of a *personalized learning experience* (p. 18). Chatti and colleagues (2015) recognized learning analytics as a "… multi-disciplinary field involving machine learning, artificial intelligence, information retrieval, statistics and visualization" (p. 1). Educause (Bichsel, 2012) included prediction in their definition of analytics (p. 6):

> Almost everyone agreed that analytics is a process that is more than just metrics. They described that process as (a) starting with a strategic question; (b) finding or collecting the appropriate data to answer that question; (c) analyzing the data with an eye toward prediction and insight; (d) representing or presenting findings in ways that are both understandable and actionable, and feeding back into the process of addressing strategic questions and creating new ones.

Barneveld, Arnold, and Campbell (2012) have recognized a more encompassing definition of learning analytics delineating major stakeholders—"[the] processes of data assessment and analysis that enable us to measure, improve, and compare the performance of individuals, programs, departments, institutions or enterprises, groups of organizations, and/or entire industries" (p. 4). The authors sorted, clarified and distinguished various categories of learning analytics into a typology based upon their intended focus (whether it be the learner, instructor, department or institution) (see Table 2).

Table 2

Typology of Learning Analytics

Type	Functions	Focus
Academic analytics	Predict student academic difficulty; emphasis on academic issues and student success; predictive modeling; determine which students are at risk; emphasis on data mining	Learner and instructor
Learning analytics—academia	Evaluate advancement, predict performance; identify issues; identify needed instructional and support resources; tailor educational opportunities; assessment; observe learning behaviors; interventions	Learner, instructor, department, and institution
Learning analytics—industry	Focus on the learners; integration of databases to create a real-time assessment of students' progression; train and develop employees	Learner, instructor, department, and institution
Predictive analytics	Prediction of success/failure; inferences about current and future events; manipulation of data leading to action	Learner, instructor, department, and institution
Action analytics	Identifying the need for reinvention; synthesis of new analytic tools	Institution and instructor

This typology categorized five differing types of learning analytics used in higher education, each with their own latent and manifest functions. The student, instructor, department and the institution have been noted recipients of the affordances of learning analytics. Reflecting upon the expansion of learning analytics into assessment and prediction, Baker and Siemens (2012) postulated,

As analytics of learning move into a broader range of settings such as informal interactions through peer networks in universities, workplace learning, or lifeline learning—educational data mining and learning analytics can help to evaluate how learning happens across various settings and how patterns of engagement or predictions of success differ in distributed versus centralized learning systems." (p. 11)

The definition and focus of learning analytics have evolved over the years. Larusson and White (2014), contend that learning analytics should include educational communities. The *1st Conference on Learning Analytics*, as cited by Ellis (2013), included the optimization of learning as an important affordance of learning analytics. Educause, in their *2015 Study of Learning Analytics in Higher Education*, distinguished learning analytics as being student centered while institutional analytics have been geared toward the business side of the institution (Arroway, Morgan, & O'Keefe, 2016).

According to *The Horizon Report* (Johnson, Adams Becker, Estrada, & Freeman, 2014) learning analytics have entailed the "… [use of] data analysis to inform decisions made on every tier of the education system, leveraging student data to deliver personalized learning, enable adaptive pedagogies and practices, and identify learning issues in time for them to be solved" (p 38). Campbell, Deblois, and Oblinger (2007) affirmed, "Analytics marries large data sets, statistical techniques, and predictive modeling . . . to produce actionable intelligence" (p. 42). These definitions are consistent with the use of *big data* to realize trends and *small data* to influence teaching and learning.

Broadening the definition of learning analytics to incorporate *business intelligence*, Papamitsiou and Economides (2014) and Chatti and colleagues (2015) defined learning analytics

in terms of strategic planning with informational technology. May (2011) ascertained that learning analytics have been jointly descriptive (what will happen) and predictive (what can be done). The Signals project at Purdue University (2013) capitalized on the principles of business intelligence to enhance student success through *actionable intelligence*.

Scholars, researchers and practitioners have created a myriad of definitions and purposes for learning analytics. Even though descriptions vary, the main ideas have remained constant. According to Romero-Zaldivar and colleagues (2012), the goals of learning analytics have centered upon the use of data and observations to impact student learning, teachers' practice and the learning process within the institution. These definitions, purposes and affordances have represented the use of data as serving three primary functions—informed teaching practice, improved students' learning and institutional preparedness and documentation.

Learning Management Systems

Learning management systems have been referred to as virtual learning environments, platforms or centralized web-based learning systems. The use of learning management systems has become widespread throughout institutions of higher learning. *The ECAR 2014 Faculty Technology Study* (Dahlstrom et al., 2014) with data from 151 institutions of higher learning, and responses from over 17,000 faculty members spanning countries across the globe, offered relevant information about learning management systems. This study emphasized the prominence of learning management systems as being essential to students' learning experiences as well as faculty teaching practices, since 99% of institutions of higher learning reported having one in place.

Learning management systems have been widely used by institutions of higher learning and have afforded instructors the ability to host courses, assignments, syllabi, assessments,

discussions, and other tools of learning in a unified and convenient location. Learning management systems house the most widely used learning analytics (Chatti et al., 2015). Blackboard has dominated the market of learning management systems although their overall market share has declined in part to the advancement of other vendors such as Desire to Learn, Canvas, and other proprietary platforms (Dahlstrom & Brooks, 2014).

Studies have reflected upon the use of learning management systems and student outcomes. Lee and colleagues (2016) found that both student and instructor learning management system usages were associated with students' final grades. MacFayden and Dawson (2010) analyzed data extrapolated from the tracking Blackboard logins at the University of British Columbia. They developed a model of student achievement by tracing factors pertinent to the professor's purposes, course design, and tools employed. A positive correlation with tracking data and students' final grades and cumulative time spent within the learning management system were not significant predictors of student success (grades). The researchers discovered that (a) student engagement between peers and with the professor, (b) the completion of optional quizzes (self-tests), (c) active participation in discussion boards, and (d) the exchange of email messages were predictive of higher achievement. While the authors pointed out that these findings have appeared intuitive, they insisted that the rapid identification of disengaged students was critical. Recognizing disengagement, and then acting upon it, were identified as key factors in preventing attrition.

Learning analytics in learning management systems. Learning management systems have built-in learning analytics, allowing the organization, calculation and display of students' activity and performance in terms of (a) time spent on discussions, assignments or assessments, (b) messages posted, and (c) pages visited, etc. Performance and activity have not only been

monitored, but quantified, assessed and displayed in logical formats (Pardos, 2013; MacFadyen, 2010; Romero-Zaldivar, 2012). Blackboard and Canvas (as well as other learning management systems) have offered educators differing types of learning analytics in numerical forms (often as an Excel spreadsheet), charts, visual displays, and in dynamic graphs (*Blackboard Analytics for Learn*, 2016; Canvas, 2016). These analytics have afforded an added dimension into the activity and performance of students. The analytics have been hyperlinked in some of the learning management systems to the homepage of the course resulting in the ease of use.

Online instructors teaching fully online or in hybrid classes have benefited the most from these analytics, although campus instructors have also reaped the benefits if assignments, quizzes, and learning materials were housed within the shell. Whether teaching online or through a campus setting, analytics have been used to monitor students' usage per day, the number of page-views, and total time spent within the learning management course. Instructors have the capacity to monitor single student's usage by clicking on their name, often revealing more in-depth information. Instructors have also used analytics to make comparisons between not only students, but classes of students during a defined time period, and also students from semester to semester.

Canvas (2016), a learning management system, coined the term *course analytics* to refer to their collection of analytic tools to gauge student engagement and performance. Canvas hosts a myriad of course analytics. Students' participation in the course has been color coded, allowing instructors to reflect upon the percentage of assignments that were submitted by students on time (green) versus those that were late (red). The graphs have been used to determine those assignments unpopular with students as indicated by a red coloration. Grades have been portrayed graphically with a thin vertical whisker extending from the lowest score for any

student in the course to the highest. The extension of the whisker extended from the 25th percentile to the 75th, and has the median marked with a short line. Instructors have access to the mean and outlying scores as well.

Canvas has offered a set of bar charts for each student in the course. These charts have identified (a) the number of page views by the student, (b) their calculated level of participation, (c) the timeliness of their assignment submissions, and (d) overall score. At a glance, instructors have access to up-to-date analytics rendering complex interactions into manageable constructs.

Quiz score statistics have been embedded into the assessment features of some learning management systems. These analytics have been constructed to convey the average score, range of scores, standard deviation, and average students' time spent on each assessment. For each individual question on an exam, the difficulty, discrimination indexes, as well as the means and modes of each test question have been provided by some of the learning management systems so that the instructor may evaluate the effectiveness of each exam question.

The promises of learning analytics in higher education. Interest in learning analytics has surged; this momentum has been due in part to technological advancements in tools available to students, instructors and researchers (Baker & Siemens, 2011; Larusson & White, 2014). *The Horizon Report* (Johnson et al., 2014) recognized technologies that exhibited a strong potential for positively impacting higher education in the upcoming years. The selection panel consisted of 53 technology experts from countries around the world. The main criterion for the addition of a technology by this organization was its plausible influence on teaching practices and student learning. Johnson and colleagues (2014) agreed that the rise of intelligence that is *data-driven* (referring to learning analytics) has the potential of fueling substantial changes in higher education within the upcoming years.

According to Baker and Siemens (2012), an affordance of learning analytics has been the concentration of students' data in one location, allowing for the inducement of judgments and informative change. Dietz-Uhler and Hurn (2013) suggested that learning analytics have the capability of increasing awareness and reflection. Mat, Buniyamin, Arsad, and Kassim, (2013) focused upon instructors' practice and achievement, issued, "It is a proven approach to predict and monitor students' performance, enable and target intervention across the learning process, and improve student and faculty success" (p. 237).

Papamitsiou and Economides (2014) have professed that learning analytics have not only informed but empowered all major stakeholders within the institutional setting. Analytics have been designed to aid instructors, departments, colleges and universities by improving student success. Real-time data has been used to identify patterns of student activity and performance, thereby rendering the capability of instructors, departments and institutions to use this data in actionable ways (Bichsel, J., 2012b; Purdue University, 2013; Dietz-Uhler & Hurn, 2013; Clow, 2012).

Clow (2012) developed a typology of learning with analytics focusing on the affordance of intervention. Learning typically originates with a student's participation in a course. When courses are housed in learning management systems, data about the student's activities, grades, and time spent in the course (for example) are aggregated. Learning analytics have been used to compare outcomes and provide a visual picture of performance and activity. Based upon the information gathered from the analytics, instructors may choose to initiate intervention if necessary. Intervention may (a)be individually based, (b) directed to a class or group of students, (c) include enhanced learning materials, and/or (c) include the recycling of information. The

provision of intervention is not targets the student, but it also results in the accumulation of more data. The cycle continues until the learning has concluded (see Figure 4).

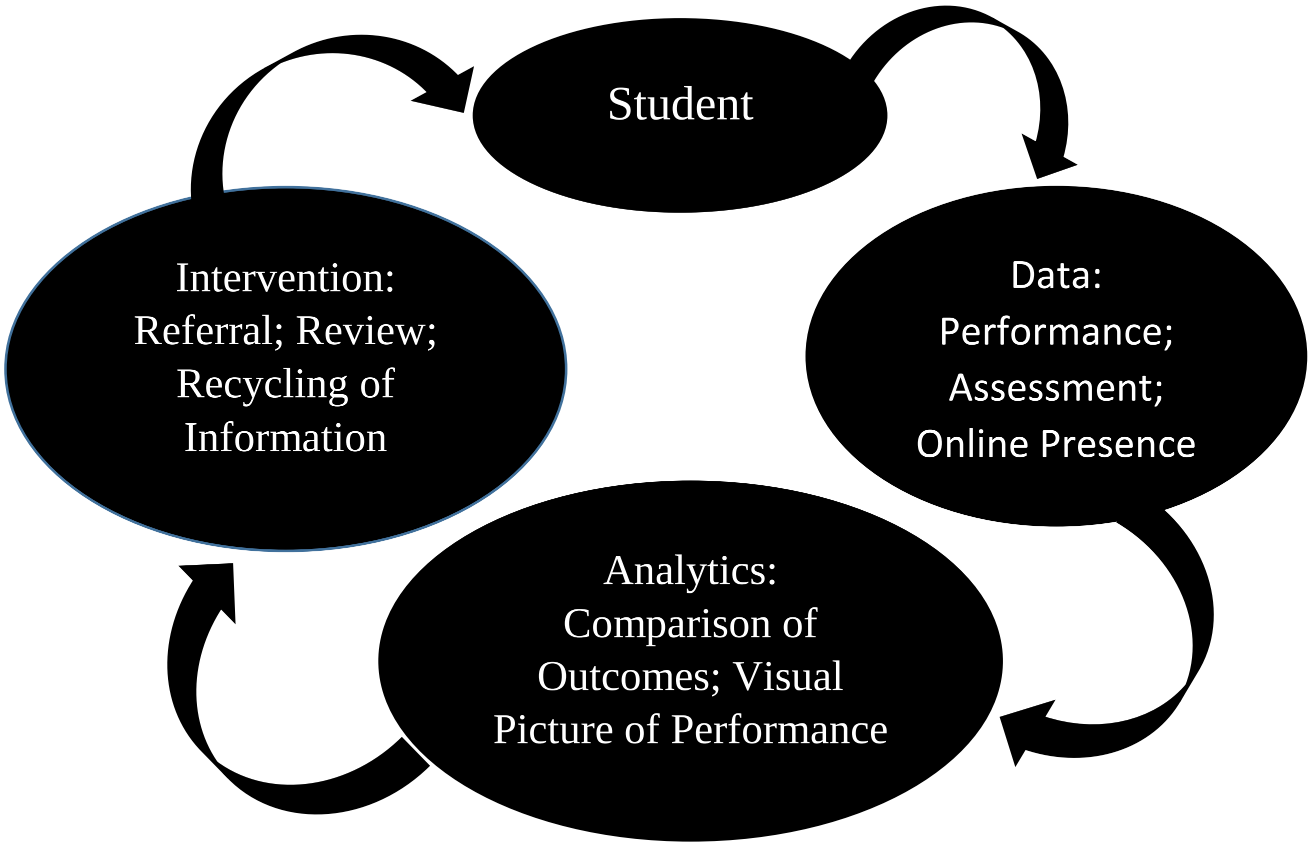

Figure 4 The cyclic use of learning analytics. The use of data and metrics to inform intervention to impact learners (Clow, 2012, p. 134).

Other researchers have reflected upon the cyclic nature of learning analytics. Concurring with Clow (2012), Oblinger (2007) reflected upon the affordances of prediction, action and change. Romero-Zaldivar and colleagues (2012) avowed that learning analytics have enabled instructors to sit in a *privileged position*; yet, they professed that this scenario is far from reality:

> An important factor that contributes toward the effectiveness of a learning experience is the ability of instructors to monitor the overall learning process and

> potentially act based on the observed events. In the ideal situation, an instructor monitoring all the events taking place in a learning environment would have a privileged position to adjust whatever parameters are available to improve the overall experience for the students. But this hypothetical scenario is still very far from reality in today's educational institutions and, even worse, there are several forces pulling away from this objective. (p. 1)

Papamitsiou and Economides (2014) directed a rigorous review of literature on the empirical evidence supporting the use of learning analytics in higher education. Their study suggested four key capacities: (a) pedagogy, (b) teaching and learning, (c) online learning, and (d) resource management. A significant reason for the institutional use of learning analytics have been attributed to a demand for accountability especially in terms of online learning. While documenting student performance, learning analytics have provided continuous credentialing that accrediting agencies have directed (Dietz-Uhler & Hurn (2013).

Garcia and colleagues (2009) maintained that using data mining tools such as learning analytics could provide instructors with data that could be used to affect improvement in their e-learning courses. They distinguished between two types of recommendations—active and passive. Active recommendations imply a direct modification of an exercise, question or perhaps a course, while a passive modification targets more generalized issues. Dietz-Uhler and Hurn (2013) suggested that the use of intelligent data generated through a learning management system should be used by instructors to provide personalized learning experiences.

According to Lykourentzou and colleagues (2009), the increasing attractiveness of online education has created a need for accurately predicting student performance. These researchers, conducting a study at the Multimedia Technology Laboratory of the National Technical University

of Athens, recommended the use of feed-forward neural networks to predict final grades. They found promising results as early as the third week in the term. Lykourentzou and colleagues (2009) found that “The neural-network technique was more efficient in mapping the nonlinearities that relate student performance during the course to their final achievement and thus provides a considerable more accurate estimation of final student grades” (p. 378). This methodology enabled instructors to provide customized assistance as it related to the students' predicted level of performance. Although they noted that this method should support instructors, they did not specify how this might take place. Furthermore, given the extensive use of statistical analysis in this study, it would be suspect if mainstream instructors would have the knowledge or ability to make sense of the complicated statistics.

Dietz-Uhler (2013), acknowledged the work of several institutions of higher educational institutions for their use of learning analytics in the advancement of teaching and learning. Six of these institutions are listed in Table 3.

Table 3

Learning Analytics Initiatives in Higher Education

University/College	Learning Analytic Tool	Focus of Analytics
Rio Salado College	PACE and RioLearn	Track student progress and provide intervention
Northern Arizona University	GPS	Alerts
Purdue University	Signals	Early warning system
University of Michigan	E-Coach	Intervention
University of Maryland	Blackboard	Trajectory of performance
Baltimore County	Check My Activity	Predict student success

These six institutions have implemented learning analytics or piloted initiatives targeting teaching, learning, student success, and/or retention measures. These will be explored further in this study.

Learning analytics and student retention. According to MacFayden and Dawson (2010), four key developments have emerged over the recent years in reference to technology enhanced learning. These include, (a) the integration of technological advances into teaching and learning, (b) the improved accessibility of learning management systems tracking data, (c) the development of learning analytics, and (d) better emphasis on student learning communities. Studies have suggested that learner determination, goal commitment, and engagement with peers and instructors— have a positive impact upon retention (Campbell, Deblois, & Oblinger, 2007; Campbell & Oblinger, 2007; Carmean, Frankfort, Haynie, & Salim, 2012; Dietz-Uhler & Hurn, 2013). Learning analytics have appeared as a vehicle by which instructors measure educational

activities by assessing the level of interaction, engagement and community. Accordingly, researchers and scholars have reported that learning analytics have the capacity to impact student success— leading to higher retention (Dietz-Uhler & Hurn, 2013; Frankfort et al., 2012; Purdue University, 2013). Specifically, researchers have presented the affordances of an early-warning system for determining students are at risk—thereby providing a safety net for students that may be struggling (Baker & Siemens, 2011; Lykourentzou et al, 2009; MacFadyen, 2011; Purdue University, 2013; Romero-Zaldivar, 2012; Wolff & Zdrahal, 2012). Recent studies relating to learning analytics initiatives at institutions of higher learning follows.

The University of British Columbia, Canada. MacFadyen and Dawson (2010), through network analysis of asynchronous course discussion boards at the University of British Columbia, identified disengaged students through patterns of communication found within the learning management system. According to the researchers, "This model suggests that students in this course who take the opportunity to engage with peers via discussion, actively engage with course materials and stay on top of administrative details relating to their participation, achieve higher overall final grades" (p. 597). This study acknowledged the analysis of five classes over three terms of undergraduate biology. Yet, the discussion forum data was only extracted from one section of 36 students. It is unclear why all five classes were not analyzed. The authors maintained, "Moreover, this mode of analysis and network visualization affords contemporary teaching staff early opportunities to adapt their teaching practices in order to meet the changing learning dynamics of a given student cohort" (p. 596). With the advanced statistical knowledge required for ego networking, it remained unclear whether instructors could implement type of analysis. It is important to note that Ramos and Yudko (2008) suggested that tracking student page views within the learning management system was a better predictor of success than discussion forum postings.

The Open University. The Open University has been acclaimed as the largest distance-based institution in the United Kingdom, boasting more than a quarter million students with thousands of instructors. Learning modules have been offered primarily through a learning management system. Utilizing learning analytics, researchers identified at-risk students and targeted intervention to prevent attrition (Bichsel, 2013; Wolff & Zdrahal, 2012). The key finding of this investigation involved the analysis of students' presence in the learning management system. In this study, students often exhibited consistent usage patterns until they hit a problem–and at that point, the student's usage decreased significantly. They referred to this as *performance drop* (Wolff, Zdrahal, Nikolov, & Pantucket, 2013). According to Wolff and Zdrahal (2012):

> Students have their own learning profile that doesn't necessarily match up against any norm. Some students click a lot and achieve very good results; others click very little and achieve the same results. Therefore, better predictive power is gained by detecting changes in a student's behavior compared to their own previous behavior, rather than trying to build a profile of an "average student" as a benchmark. The variability among learners, at least on the VLE, seems too great to make building the profile of the "average student" a viable option. (para. 24)

Wolff and Zdrahal (2012) proposed that the identification of performance drop resulted in the accurate prediction of problems; instructors could then strategically target interventions toward students requiring the most attention. It remained unclear as to the extent and nature of lecturer involvement in this endeavor. The authors used GUHA (General Unary Hypothesis Automation) as a method of data analysis and reported that analytics helped to illuminate problems and predict drop-out. Acknowledging limitations, Wolff and Zdrahal (2012) stated,

> Similarly, there is a need to take into account the interplay between how a module is structured and how the VLE [virtual learning environment] is intended to be used within that structure. This is especially true when making predictions using VLE activity, since it could easily be some feature of a particular module that influences VLE behavior, such as an assessment has been made deliberately easy (which could mean less required activity) or else a lot of module materials need to be read or referenced for another (thereby increasing activity for that TM(A). (p. 4)

Therefore, an easier module may have inaccurately reflected students' performance drop. Although they claimed the predictive model offered promising results, they did not reflect upon the instructors' role nor the students' usage of the data to inform the learning process; nor did they offer these as suggestions for future research.

Northern Arizona University. Northern Arizona University incorporated an early- warning and retention system—Grade Performance System—utilizing analytics to predict student outcomes. Depending upon the nature of the alert, students received a number of resources, including deadlines, supportive and beneficial links, and other action prompts to help resolve academic issues. Students received feedback through e-mails sent from the instructor. This system also alerted other university personnel for possible action or intervention. According to the university, messages were posted in the students' MyNAU portal prompting them to check their e-mail. A permanent record was generated within the system so that instructors and other personnel could review and necessitate or implement action (Collette, 2010). Even though instructors were informed to send only one message to each student per week, additional messages could be sent to subgroups of students (Picciano, 2012). It was purported that this initiative led to a significant decrease in failing grades and withdrawals (Northern Arizona University, 2015). The findings suggested that increased

instructor and student interaction, coupled with supportive interventions to at-risk students, positively affected their academic outcomes, course retention, and graduation rates (Collette, 2010). It is important to note that the use of this system was voluntary and the nature and extent of instructor participation was not clarified in the literature.

Learning analytics and student outcomes. Learning analytics have enabled the assessment of learning activities through the measurement of student collaboration, engagement, and community. Performance data mined in the learning management system have been used to predict performance and to make data-driven choices—thereby affecting change and impacting student outcomes (Bienkowski, Feng, & Means, 2012; Dietz-Uhler & Hurn, 2013; Purdue University, 2013).

According to Baker and Siemens (2012), the purpose of prediction is to successfully support interventions to measure and impact student outcomes. Multiple variables have been analyzed and gauged as performance indicators; these have included grades, portfolios, skills, enrollment, online presence, engagement in learning activities, and students' action within the learning management system. In this manner, learning analytics have been utilized to monitor progression in the course and measure student learning outcomes (Baker & Siemens, 2011; Lykourentzou et al., 2009; MacFadyen, 2011; Purdue University, 2013; Romero-Zaldivar, 2012; Wolff & Zdrahal, 2012).

Other researchers have explored students' usage logs within learning management systems. Ramero-Zaldiver et al. (2012) tracked *work-time events* within learning management systems to gather data on performance. The students with the greatest usage were selected to derive the predictive model. They found that the observations of students' activities within their own personalized working area offered a trustworthy context to predict academic success. Baker and Siemens (2012) concluded that learning analytics have been used to successfully determine the

source of students' disengagement including boredom, *gaming the system*, non-task behavior, and sloppiness. Baker and Siemens (2012), however, failed to provide information on the targeting of students, how the off-task behaviors were determined, and what type of interventions were undertaken to promote learning outcomes.

According to Papamitsiou and Economides (2014), *machine-readable data* has been used within the educational setting to reflect upon teaching practices and impact modification of course designs. Garcia and colleagues (2009) claimed that recommendations retrieved from data were either active (implying a direct modification of the course) or passive. It has been reported that the use of data have offered the potential of expediting program and degree completion while advancing student outcomes. In this manner, learning analytics have the potential to benefit all stakeholders within the institution including the student, instructor, department, bodies of governance, researchers, and the institution as a whole (Johnson et al., 2016).   It is important to note that although these claims were purported, the literature did not offer *how*, *when* and *who* would implant change.

Purdue University. Purdue University (2013) implemented a learning analytics initiative in the form of predictive algorithms in their Signals project. Student performance, earlier educational history, and other variables were conglomerated; sense-making of the data was undertaken with algorithms. The end result was displayed in the form of a traffic light to the students (red, yellow and green). A red light offered the student a timely warning indicating some type of issue or danger in the course. A yellow sign represented a warning; a green light was an indication that the student was achieving or performing adequately. This project was based upon the premise that students often do not understand their progression or lack of advancement in an online course. According to this study, (Purdue, 2013) the use of analytics resulted in (a) a significant increase in students

receiving A’s and B’s in the courses, (b) a significant decrease in failures and withdrawals, (c) a significant increase in retention, and (d). a greater likelihood of matriculation if two or more Signals courses were taken. It was not clear as to the nature and extent of instructors’ buy-in at Purdue University (2013), since “Instructors can decide to intervene through posting the signal on the student’s home page, emailing them, texting them, referring them to an academic advisor or resource center, or scheduling a face to face meeting with them” (p. 3). Purdue University (2013) did not comment on the nature and extent of instructors’ participation, other than generalized references such as “… while some of the instructors” (p. 4) or “Instructors meanwhile agreed…” (p. 5). As conveyed in the literature, the burden of consideration of these color-coded analytics was upon the students’ shoulders and not necessarily the instructor.

Rio Salado College. Smith, Lane, and Huston (2012) conducted a case study at Rio Salado College utilizing their learning management system (RioLearn) and final grades (through PeopleSoft). Rio Salado College boasted the largest reported student enrollments in the state of Arizona. This institution has been considered a pioneer in early learning analytics, data mining, and predictive modeling. The purpose of their research was to isolate variables that elicited significant statistical correlations with course outcomes. Analysis of the frequency of logins, engagement, student pace, and scores were identified as predictors of course outcomes. Some of the variables of importance included the students’ viewing of the homepage and syllabus, opening and completing assessments, checking their grades in the gradebook, assessing their feedback, opening a lesson or assignment, and checking due dates on calendars.

Smith and colleagues (2012) suggested that recent behavior is more significant than past behavior when analyzing course outcomes. A Naïve Bayes classification model was used to construct classifiers. A multiple-level warning system was utilized to provide an estimation of the

probability of course success, with warning levels categorized from low to high. RioPACE (Rio Salado Progress and Course Engagement) was built into their learning management system, delivering designated warning levels weekly based upon analytics. The chairs of departments were encouraged to design a student success intervention strategy and act upon predictions generated on the eighth day of class. The researchers found that an early login to the learning management system and low warnings were predictive variables of success. The authors purported that predictive modeling was effective in correctly gauging the probability of student course completion. This case study, according to the researchers confirmed the positive correlation that exists between some learning management system variables and course outcomes. Furthermore, they posit that some variables may serve as early-predictors of course completion or dropout. Although the researchers proclaimed that the objective of the study was to facilitate the connection between instructors and at-risk students, there was little other mention of instructors in their literature. More specifically, Smith and colleague (2012) speculated, “We theorized that instructors might be able to launch more customized interventions for at-risk students if they had information showing student performance within specific LMS activities” (p. 55). It is important to note that the researchers did not find that their initiatives generated substantial increases in retention and success due to the difficulty of the faculty contacting students via telephone. It was also interesting that the Smith and colleagues (2012) stated (at the end of the article), “A summary of two initial intervention pilots was provided showing occasional positive results” (p. 60).

Harvard University. Harvard University mined classroom tracking data using the *Learning Catalytic System*. This internet-based platform provided an interactive student-response tool supporting peer instruction as a method of teaching, allowing immediate feedback during class. Students logged into their virtual classroom through computers or mobile devices and accessed

information in the form of problems or open-ended questions presented by the instructor. Once the student answered the question, the system analyzed the answers and then paired the students into study units. The students were instructed through a series of messages on their paired-learning partners, encouraging team-based learning. The instructors received a diagram portraying students' answers. Based upon these answers, the instructors could choose to provide intervention. This type of system, coupled with instructor's intervention, provided customized support to the students in a timely manner (Pearson Publishing, 2015; Stark, 2015). This initiative was purchased by Pearson and is now offered free to Harvard students and instructors (Mazur, King, & Lukoff, 2016; The Academy at Harvard Medical School, 2013). It was unclear as to the extent of buy-in by instructors and students at this institution before and after its inclusion in the umbrella of Pearson Publishing's products.

Paul Smith's College. Paul Smith's College, a small, private, nonprofit institution was faced with significant issues regarding student success and retention. A large number of their incoming students were academically underprepared and unequipped to handle the rigor and pace of higher education. In response, the college instituted a campus-wide task force examining the issues, implementing a *Comprehensive Student Support Program*. Identifying several primary challenges, they found that data were not used efficiently to identify at-risk students. To support those initiatives, they used *Rapid Insight's Veera and Analytics Programs*, *Starfish Retention Solutions Early Alert*, and *Connect* programs to improve their early-warning system—offering more competent identification of students at-risk. The college combined differing file types and formats under a single umbrella—automating reports and using predictive modeling to detect students in danger of failure. These reports, prioritizing students' needs—were distributed to key stakeholders for the purpose of intervention. The data suggested that these methods resulted in larger gains in

student success (Bichsel, 2012b; Taylor & McAleese, 2012). It is important to note that this initiative involved an automatic distribution of information to the key stakeholders (including instructors). It was unclear whether the instructors reflected upon or to what extent they used this information proactively to inform teaching and learning.

The University of Washington in Tacoma. The University of Washington in Tacoma launched an online initiative for introductory math courses (Bichsel, 2012b; Frankfort, Salim, Carmean, & Haynie, 2012). Cognizant of meager academic performance in lower-division online math courses, the university developed a research-based support structure to promote student learning outcomes. Instituting a pilot collaboration with *Persistence Plus*, online math students were offered behavioral intervention in the form of daily *nudges*—delivered to their personal mobile devices. Support was personalized and based upon individual student's course performance and assessment grades. Nudges consisted of research-based questions and messages designed to encourage positive academic behaviors. The use of learning analytics to automate behavioral nudges were positively correlated with increased student outcomes. In two math courses, students participating in the pilot program achieved higher course outcomes than students outside of the study. Nudges encouraging engagement in study groups often compelled online students to congregate and prepare for upcoming exams (Bichsel, 2012b; Frankfort, Salim, Carmean, & Haynie, 2012). This pilot study involved 85 students in an introductory math course. Frankfort et al. (2012) stated, "UWT's e-learning initiative worked closely with the math program, and Persistence Plus coordinated with a math instructor to ensure alignment and proper collaboration of effort, thereby gaining the buy-in often missing in the analytics movement" (para. 9). Yet, it was unclear how the participation of one instructor gained the buy-in as proclaimed.

University of Michigan. The University of Michigan, a large public institution, adopted *E2Coach* (with Educause's Next Generation Learning Challenge program) providing personalized messages and data graphics to students in large STEM courses of over 500 students. The university instituted this service since the large classes made personalized communication between the students and the instructor, difficult at best. E2Coach was designed to support at-risk students and encourage them to persevere through the use of a web application supported by the Michigan Tailoring System. The system addressed students by their first name and tailored messages based upon information retrieved from the registrar, survey responses, and the gradebook. This warning system differed from other analytic initiatives in that each message was addressed to one specific student, not to an entire class or subpopulation. The findings concluded that increased student access to E2Coach and the tailoring system resulted in students outpacing their incoming grade point average (Vinson et al., 2011). The authors suggested limitations to this study, including the cost, logistical concerns for large scale implementation, intervention, and integration. The extent and nature of buy-in by instructors were not addressed.

***University of Maryland, Baltimore County.* Since 2007, the University of Maryland, Baltimore County had noted a correlation between failing grades and lower students' usage of their learning management system—Blackboard. Researchers analyzed correlations between students' tracking data and their performance. The researchers explored *if* and *how* learning analytics could help at-risk students through the use of peer-related feedback as an intervention strategy. The university conducted a survey to evaluate students' help-seeking behaviors. Of the respondents, 30% used the feedback tool, and of them, 63% earned a passing grade of C or higher (Fritz, 2013; Mat, Buniyamin, Arsad, & Kassim, 2013). Approximately 70% of the students did not use this tool and the study did not reflect upon**

instructors' use of learning analytics to inform intervention. Furthermore, the research stated, "If instructors post grades online, the CMA [Check My Average] will also compare a student's activity with the average activity of this or other course peers earning the same, higher, or lower grade for any assignment" (p. 2). Consequently, the buy-in of instructors was unclear as it did not denote the number of instructors using this tool.

Prioritization of Learning Analytics

As learning analytics have developed, universities have garnered greater access to tools, learning management systems, and data needed to personalize the individual student learning experience (Johnson, et al., 2016). The EDUCAUSE Center for Applied Research (ECAR) released a report on the current state of learning analytics—*Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations* (Bichsel, 2012). Data for this study was collected through surveys and focus groups with informational technology experts. According to Bichsel (2012), 69% of the responding institutions in the *ECAR Study* viewed learning analytics as a chief priority for some divisions or programs (with 28% reporting that it was a chief priority for the entire organization). A low number (six percent) of the responding institutions conveyed that learning analytics are not a significant interest. Larger educational colleges and universities placed a greater priority on learning analytics than those that have lower enrollments. According to Bichsel (2012), :

- analytics were most successful when departments have partnered;
- compared to other areas, investment in analytics has made the least progress;
- institutions should invest in experienced personnel rather than the acquisition of additional technologies or the further collection of data;
- progressive institutions have used data to promote prediction, action and change; and

- the majority of participants in focus groups believed analytics usage would continue to grow in the upcoming years.

One of the survey questions on the instrument referenced whether the faculty largely accepted the use of analytics. An interesting finding from the report suggested that analytics gained the least acceptance among instructors. A failure of instructors to utilize learning analytics primed the following discussion on the rhetoric of learning analytics in higher education.

The Rhetoric of Technology and Learning Analytics

Dating back to the early 1990's, researchers and scholars have reported on the use of technology including preservice teacher preparation, expectations and realities (Strudler, McKinney, Jones, & Quinn, 1999; Strudler & Wetzel, 1999). Strudler and Wetzel (1999) argued that an informed strong committed leadership of the faculty chairs and administration was crucial to technology implementation, suggesting:

> At the core of informed leadership is a person who has internalized the complexity of effective technology integration and who exercises influence over time to ensure that the various enabling factors are in place or being addressed. Further, knowledgeable leaders articulate the technology, teaching vision, and goals of their colleges. (p. 68)

In this connection, knowledgeable leadership helped to establish a unified vision and mutually satisfying goals for the institution.

Strudler and Wetzel (1999) and Strudler and colleagues (1999) suggested that additional impediments to integration have often been due to a lack of resources including the allocation of technology and computers in the classrooms, professional development and technical support. Strudler and colleagues maintained, "Technology integration is dependent upon adequate computer resources, faculty development opportunities, and onsite support–all of which require

funding" (p. 125). Strudler and Wetzel (1999) conveyed that professional development must allow for the integration of technology into the curriculum and not merely serve as an add-on. Professional development should include workshops, hands-on opportunities, group classes, and comprehensive training. Furthermore, offerings were most effective when they accommodated a variety of work schedules and provided pedagogical support. According to Strudler and Wetzel (1999), simply knowing the tools of technology, was not indicative of the instructors' ability to use technology affectively to influence students' learning and enhance their own current instructional style. Strudler and colleagues (1999) suggested that training to teach with instructional technology trailed behind other teaching practices, surmising: "Findings of the current study are consistent with the mounting evidence that beginning teachers are not being adequately prepared to teach with computers and related technologies" (p. 124).

Instructors must recognize the fit between the method of teaching with technology and learning (Strudler & Wetzel, 1999) . This is often referred to as *pedagogical fit*. Strudler and Wetzel (1999) insisted that (a) one-on-one support with instructional specialists, (b) consulting, (c) modeling of technological applications, (d) offering alternative teaching styles, (e) presenting a good balance between pressure to implement versus encouragement, (f) and an open door policy for assistance were crucial components of the implementation process.

Strudler and Wetzel (1999) further implied that grants and institutional wide initiatives should be afforded to instructors choosing to bolster their technological skills. Stipends, workshops (during and inbetween semesters), sabbatical leaves, technology access, and initiatives that encouraged instructors to share their knowledge with others afforded optimal implementation. In their study of four colleges of education with exemplary technology focus, Strudler and Wetzel (1999) found,

> None of the colleges reported that technology was directly considered in its traditional reward structures for faculty tenure, promotion or merit. Several stated, however, that inasmuch as technology can impact good teaching and scholarship, it can contribute indirectly to faculty rewards, but there was no evidence that any of the colleges had plans to directly link these rewards to technology use. (p.74)

Strudler and Wetzel (1999) argued that instructors often lacked the time needed to learn and implement technological advances. Often, when instructors used computers, they rarely ventured beyond a minimal investment of time and energy, mainly creating documents or practice activities.

Each university has a unique culture that prioritizes that which is deemed necessary and important. Even though individual instructors have exhibited their own beliefs about technology—the institutions' culture has often overshadowed. Institutions have recognized the impact of learning analytics on the field of teaching and learning; however, instructors' usage has been underexplored and often criticized as being simplistic—reducing the learning process to a series of clicks needed to generate a grade (Bischel, 2012b; Fritz, 2013; Wolff, Zdrahal, Nikolov, & Pantucket, 2013). Underuse has been attributed (a) to the culture of the institution, (b) to instructors' lack of knowledge of what to do with the data once it has been collected, (c) the use of data mainly for administrative purposes, and (d) resistance to change (Campbell & Oblinger, 2007; Ellis, 2013; MacFadyen and Dawson, 2012; Stiles, 2012). Reluctance of instructors to use their institution's learning management system has been cited as a possible reason for not using learning analytics. MacFayden and Dawson (2012) found that 70% of instructors failed to use their institution's platforms, noting a staggeringly low figure. When

instructors used learning management systems, it was used mainly for discussions, organization of learning materials, and assessment.

The Learning Analytics in Higher Education Report offered the most up-to-date information on the state of learning analytics (Arroway et al., 2016). Their key findings addressed the continued issue that learning analytics have been viewed as an interest rather than a priority; usage has mainly centered on the monitoring of students to impact course completion. Furthermore, key challenges included the lack of support with institutional leadership as well as a possible culture of resistance. While instructors may have issued their support of learning analytics to improve student outcomes, their actions have often denoted the opposite—referring to this as an *action-lag* (p. 9). In this connection, Arroway and colleagues (2016) noted the reluctance of instructors to use analytics, citing resistance due to suspicious motives, insufficient or inadequate data, and a lack of interpretive value. A lack of universal buy-in—often referring to it as a focus on counting rather than a culture of measurement—was evidenced. MacFadyen and Dawson (2012) and Greenland (2011) indicated that simply monitoring login and page-visited clicks were not sufficient indicators of student investment in learning.

As the review of literature has documented, studies on the usage of learning analytics in higher education have often not cited the level of buy-in by instructors; often it was never addressed at all. An example of this is the Signals project at Purdue University (2013), in that "Instructors can decide to intervene through posting the signal on the student's home page, emailing them, texting them, referring them to an academic advisor or resource center, or scheduling a face to face meeting with them" (p. 3). No data were provided by Purdue (2013) denoting the buy-in nor nature and extent of instructors' participation other than generalized references such as "…while some of the instructors" (p. 4) or "Instructors meanwhile agreed…"

(p. 5). How many instructors agreed? It remained unclear. Purdue (2013) suggested, "No relationship was established between student success and the frequency of feedback sent in Signals messages" (p. 4). The findings of this study are problematic since the messages were the focal point of this learning analytics mission. The institution surveyed 1,500 students about their use of Signals yet the data did not reflect upon instructors' practices that would have enabled the triangulation of data. Beer and Tickner (2014) found in their study of the adoption of learning analytics at CQ University, that unless there was a plan to *do it with* instructors, initiatives have failed.

More recently, scholars have reported on conditions that have affected utilization and implementation of instructional technologies at institutions of higher learning (Bichsel, 2012, 2012b and 2013; and Mirzajanin et al., 2014) analyzed the integration of information communication and technology efforts at select universities. Significant factors affected implementation, including the availability of resources, skills, time and leadership. A factor that was noted as an impediment was the lack of a reward system for instructors (whether it be persuasion, incentives, recognition, or respect). All five of these factors were originally noted in the 1990's by Strudler and Wetzel (1999) and Strudler and colleagues (1999) reiterating the fact that while technology has continued to expand and become more complex, higher education has been struggling with the same fundamental issues. In addition, Mirzajanin and colleagues (2014) reported that "Nevertheless several universities faculty members have determined to integrate ICT (information communicaton and technology) into their training, some faculty make the purposeful selection not to do so" (p. 25).

Bichsel (2012 and 2012(b), in the *ECAR Study of Analytics in Higher Education,* reflected on the eminence of learning analytics at institutions of higher learning. Bichsel noted

that many institutions of higher learning were not yet taking advantage of learning analytic. It is important to note that the primary focus of this study involved professionals with information technology backgrounds and not necessarily mainstream instructors. Respondents indicated that evidence-based data must be provided recognizing the appropriateness of technology and its influence upon student learning. Furthermore, instructors must feel assured that the technology they use will function and operate as intended. A respondent in the *ECAR Study* (Bichsel (2012b) proclaimed, "What we have is bloated (= zillions of features we do not need), badly designed features we need are not streamlined, easy to use, [nor] intuitive" (p. 10). Bichsel suggested that instructors who used more advanced tools and analytics exhibited higher satisfaction ratings than others.

Bischel (2012b) found that most institutions have not utilized learning analytics to make predictions that could affect change. Learning analytics were found to be used most often in admissions, finance, and matriculation but have lagged behind in the areas of instructional administration, student learning, teaching, performance, and research. Ironically, Bischel (2012b) found that respondents' perceived benefits of analytics were greatest for students, even though this often was not shown as a priority. The benefits, as reported by the respondents included the consideration of students' behaviors, optimization of resources, recruitment, and affective learning strategies.

Researchers have noted problems inherent with the implementation and use of analytics, suggesting a lack of understanding and questions about the usability of the data once it has been collected. Bienkowski, Feng and Means (2012) noted that the lack of interoperability of analytics in learning management systems as well as privacy issues have been concerning. Often, the use of analytics as well as other advanced technologies have been met with resistance

and or confusion; instructors have felt that perhaps it does more harm than it does good (Al-Busaidi & Al-Shihi, 2012; Campbell & Oblinger, 2007; Ellis, 2013; MacFadyen & Dawson, 2012; Mishra et al., 2009; Stiles, 2012). Al-Busaidi and Al-Shihi (2012) found that computer anxiety negatively impacted instructor satisfaction of learning management systems. The reported issues with resistance, anxiety and confusion—often experienced with the implementation of new technology—could be addressed with supportive professional development opportunities.

Issues were inherent in some of the research offered in the present review. Some of the studies were (a) based upon small samples often including one or a few courses, (b) not longitudinal in nature, and (c) often did not reflect accurate or sufficient findings (Lykourentzou et al., 2009; MacFadyen & Dawson, 2010; Romero-Zaldivar et al., 2012). While these studies have afforded insight into technology and learning analytics, failing to offer a substantive review of buy-in by instructors and failing to reflect upon the nature and extent of instructors' use is problematic. The study at the National Technical University of Athena (Lykourentzou, et al., 2009) involved one e-learning course while the study at the University of British Columbia noted the inclusion of discussion forum data from 36 students (MacFadyen & Dawson, 2010). Romero-Zaldivar and colleagues (2012) reported a single fifteen-week study of one engineering course of 248 students utilizing a virtual appliance at the University Carlos III of Madrid. They monitored student activities, yet data was only recorded and reported for approximately two-thirds of the students. The exclusion of data for 76 students was relevant to the findings in this study; forty-six of the students dropped the course while the activities of an additional thirty students were not disclosed.

The literature often focused on a researcher's perspective involving complicated and involved statistical analyses that would often be unmanageable or not comprehendible by practicing instructors not schooled in advanced statistical analysis. A brief by *The Department of Education Brief on Learning Analytics* (Bienkowski, Feng, & Means, 2012) revealed, "Today, teachers and school leaders are surrounded by many data reports and often are frustrated by how much work is required to sort the useful from the useless" (p. 40). Lee and colleagues (2016) admitted in their study that the analysis was "…labor and computationally intensive" (p. 111) and that "… more data is not necessarily better data" (p. 113). Lykourentzou et al. (2008) used clustering, regression analysis, and neural-network approaches to determine prediction. This methodology although deemed useful by the authors, is outside of the realm of possibility for most instructors. This was likewise found with the Romero et al. (2007) study involving Moodle tracking logs, GISMO, MySQL, PostgreSQL, Weka and Keel software systems, regression analysis and clustering. Garcia et al. (2009) used data mining tools including MultiStar, EPRrules, KAON, Synergo/ColAT, GISMO, Listen tool, TADA-ED, O3R, MINEL, Simulog and Moodle mining tools (p. 299). With the usage of these complex and advanced tools, Garcia and colleagues' (2009) recommendation was interesting, "In this paper, we describe an educational data mining tool based on association rule mining and collaborative filtering for the continuous improvement of e-learning courses and it directed to teachers non-experts in data mining" (p. 299). It would appear that non-experts including most mainstream instructors would have difficulty with extensive and complex data mining technology.

An institutional focus was often presented in the review of literature. Taylor and Aleese (2012) reported that St. Paul's College had an astonishing growth of over two million dollars in net student revenue due to an improved retention of students from Spring 2010 through Fall 2011

semesters. Bichsel (2012a & 2012b), in the *ECAR Study of Analytics in Higher Education*, suggested that the majority of data collected by institutions has been used primarily for credentialing, admissions, financial aid purposes, matriculation, and research. Despite successful implementation of analytics in some institutions of higher education, Bichsel (2012b) suggested that most institutions of higher learning have analytics challenging. When data has been collected, it has often not been used at all. According to Fritz (2013):

> One factor contributing to this slow adoption [learning analytics] is often the difficulty of accessing the relevant LMS activity, demographic, and student academic data necessary for predictions. Typically, even administrators for each of these systems aren't very familiar with how they all interrelate, except perhaps to carry out basic operations like course creation and auto enrollment of students to start the semester. The task of analysis–making sense of the data, identifying key variables, developing hypotheses about critical factors that impact development and evaluation of interventions–is even more challenging. (pp. 7-8)

Chatti and colleagues (2015) delineated key stakeholders in a review of literature on learning analytics. They found that most of the studies targeted *intelligent tutors* (48%) or researchers and systems designers (30%). They uncovered few studies involving instructors' use of learning analytics to inform student performance. In like manner, a study by Barber and Sharkey (2012) on the use of course correction and analytics focused on *a few academic advisors* rather than on the instructors' teaching practices.

A student oriented focus was also found in the literature. The initiative at the University of Maryland stated that instructors were key to the identification of at-risk students (Fritz, 2013). Findings from this study reflected the opposite. Fritz (2013) acknowledged, "We believe that

students must take responsibility for their learning, and one of our approaches to intervention was to try to raise student awareness–particularly among underperforming students–by comparing their activity with higher-performing peers" (p. 2). Fritz (2013) however, mentioned the insights derived from the students may influence instructors' course design, without citing any specific data or reasoning. Fritz also reported that often—students as well as instructors—failed to respond to the system-generated feedback (without noting the nature and extent). Certainly, the failed response of instructors and students was concerning.

Trustworthiness of data was questioned in some of the studies. For example, the study at Rio Salado (Smith et al., 2012) heralded, "Predictive modeling to forecast student outcomes and drive effective interventions in online community college courses" (p.51). However, the researchers did not find that their initiatives generated substantial increases in retention and success due to the difficulty of contacting students via telephone. At the end of their article, Smith and colleagues (2012) noted, "A summary of two initial intervention pilots was provided showing occasional positive results" (p. 60). Therefore, this study offered conflicting information about the forecasting of at-risk students.

Barriers to buy-in and implementation of technologies were evident in the reviews. These included problems with the integration of technology, ethical issues, lack of digital fluency, and institutional culture (Johnson, 2010; Lane & Lyle, 2011; MacFadyen & and Dawson, 2010; Reid, 2014; Singh & Hardaker, 2014; Slade & Prinsloo, 2014). Furthermore, according to Slade and Prinsloo (2014), the literature on learning analytics has historically presented a negative snapshot—with portrayal of words like *at-risk, intervention, and under-performing*—posing students as habitual failures. Wolff and colleagues (2013) used the terms *student failure* and *ailing students* in reference to their research at Open University. The

prevalent verbiage has perpetuated the literature on learning analytics with the notion that students are passive subjects in need of intervention

Contribution to Current Literature

The findings from the present study were important as it contributed to a better understanding of the practice of learning analytics from an instructors' perspective. With the literature review, it was apparent that *select* higher educational institutions have embraced learning analytics as a means to understand students' performance. The primary focus found in the reviews centered around case studies expounding the affordances of learning analytics; often these studies were from a researcher's perspective. The present study has contributed to the body of literature on learning analytics in critical areas, including: retention and student outcomes, early-warning systems, and barriers to adoption and implementation.

Retention and student outcomes. Studies from institutions of higher education on the use of learning analytics primarily reflected upon the affordances of promoting retention and improving student success (Collette, 2010; Dietz-Uhler & Hurn, 2013; Frankfort et al., 2012; Purdue University, 2013). Although some course-design practices have been studied (such as sending nudges, having color-oriented signals, or contacting students at risk), literature reflecting upon the extent of instructors' exploration of learning analytics in their daily teaching practice was either absent, vague, or minimally addressed. Recognition and understanding of best practices has served as useful building blocks to sound pedagogical practices. The identification of learning analytics practices and corresponding intervention strategies would certainly contribute to the body of literature by presenting findings that others can build upon. These findings could then aid instructors in their pursuit of enhanced teaching practices that could effectively increase student learning outcomes and prevent attrition.

Early warning system. Several studies have illustrated the affordances of an early-warning system for instructors to determine students at risk (Baker & Siemens, 2011; Lykourentzou et al., 2009; MacFadyen, 2011; Purdue University, 2013; Romero-Zaldivar, 2012; Wolff & Zdrahal, 2012; Wolff et al., 2013). Many of the studies emphasized (a) the monitoring of students, (b) prediction of potential success (or failure), (c) intervention, and (d) the identification of effective strategies to enhance instruction. The present study contributes to the body of literature by specifically exploring the current nature and extent to which various forms of learning analytics are actually being used by instructors in practice, and whether these have been used proactively as an early-warning system.

Conclusion

The motivation for the literature review was to explore studies involving institutions of higher learning to discover instructors' buy-in and use of learning analytics. Specifics about instructors' practices were faint at best; most often the role of the instructor was diminished or non-existent. Some researchers posted findings that were unsubstantiated, based upon small sample sizes, lacked sufficient data, or involved complex statistics. Much of the focus of the literature centered around the researchers' work with advanced analytics and data mining procedures, targeting the institution or the student as the key stakeholders rather than instructors.

The literature reflected consistent findings from the 1990's until the present time, portraying implementation issues with technological innovations in higher education, including resources, skills, time, leadership and lack of a rewards system. Change has been most productive when leaders were committed to the possibility of making institutional, departmental, and even course changes. Instructors have played a pivotal role in educational technology adoption and implementation. The future of learning analytics has appeared ripe with

possibility—yet in need of caution. Members of the educational community have acknowledged the importance and significance of learning analytics, including administrators, researchers, programmers, instructors, and students. Yet acknowledging the use of learning analytics as being informative is far from actually using analytics in teaching practice.

Chapter 3

Research Methodology

The purpose of this study was to explore, discover and frame the experiences of instructors in higher educational settings in reference to their learning analytics practice. This included the nature of their patterns of use, and meaning. This chapter presented a two-phased research approach–a dominant-less dominant design as proposed by Creswell (1994). Population, setting, instrumentation, data-collection procedures, data analyses, and ethical considerations were presented. The value of this study was derived from its fit with previous research in that it filled a gap in the literature exploring the nature and extent of faculty usage of learning analytics.

Research Design and Rationale

The general research question that guided this study was the following: How do faculty members in institutions of higher education use learning analytics to explore teaching practices and learning (including retentions and increased outcomes)? Subsequent questions included:

RQ1: How do instructors at institutions of higher learning explore learning analytics in their teaching practices, curriculum, or pedagogy?

RQ2: How do instructors at institutions of higher learning explore learning analytics to influence student learning and outcomes?

RQ3: What are the perceived key challenges to the adoption or use of learning analytics by instructors at institutions of higher learning?

For the purpose of this study, learning analytics was defined according to Educause's (Bichsel, 2012) description, "Analytics is the use of data, statistical analysis, and explanatory and predictive models to gain insights and act on complex issues" (p. 6). The present study focused on the use of analytics from an instructors' perspective. An exploration of adoption,

implementation and use of learning analytics—including experiences and expectations—provides instructors and leaders in institutions of higher learning with useful information that is strategic for planning and practice.

The primary references reflected upon in the design of this study included Creswell (1994, 2012, & 2013), Englander, (2012), Marshall and Rossman (2011), and Merriam (2009). This study was purposefully designed to gather personal data through the survey process to explore adoption and the extent and nature of usage of learning analytic tools to support teaching and learning. A review of qualitative and quantitative methods was undertaken to reflect upon the best approaches for this study.

The mission of quantitative research has been to (a) provide a numerical description of respondents' experiences, (b) allow for the generalization of a large sample to the population, and (c) manipulate variables in relation to outcomes (Creswell, 1994, 2013). According to Englander (2012), quantitative measures have aimed for representativeness; external validity was dependent upon good sampling procedures. The purpose of the quantitative portion of this study was to descriptively examine the respondents' usage of learning analytics.

The mission of qualitative research has been viewed differently in that it has focused upon (a) an exploration of personal experiences, (b) the discovery and creation of one's existence, (c) the interpretation of experience, and (d) sense-making (Merriam, 2009). Investigations such as this one, have required in-depth and detailed investigation. Flexibility without rigid categorization and the exploration of meaning behind thought and experiences are necessary components of this qualitative approach (Creswell, 2012, 2013).

Since the present study required descriptive analyses of variables and an exploration of the phenomenon, a two-phased research approach (a dominant-less dominant design) was chosen

(Creswell, 1994). This design incorporated a central paradigm (survey research) with another component of the study drawn from phenomenological research.

To obtain a thick description of the situation, Creswell (2012), and Singleton and Straits (2009) suggested the examination of thoughts, feelings, and actions. The present study explored the complex issue of learning analytics through the lived experiences of instructors; shared experiences have enabled an understanding of the phenomenon. Simon (2011) stated, "Phenomenological research is people's experience in regard to a phenomenon and how they interpret their experiences" (p. 105). According to Marshall & Rossman (2011), phenomenological approaches have involved exploration, description and analyses with a focus on the psychological aspects of perception, judgement and sense-making. This enabled the examination of the phenomenon under investigation, and not just an analysis of the instructors; however, the instructors were required to describe the phenomenon (Englander, 2012). Formal interviews and open-ended questions were used as tools to elicit a thick description of the phenomenon (Creswell, 2012). In this manner, a phenomenological approach allowed the unveiling of themes and nuances so that a robust description of their lived experiences was presented (Englander, 2012; Singleton & Straits, 2009).

The dominant-less dominant design approach was advantageous as it provides a more in-depth and consistent picture of instructors' lived experiences in reference to their teaching practices. A disadvantage of this method is that purists of both of these approaches may consider it a misuse of their respective paradigms.

This study has reflected upon change theory and TPACK. Ertmer and Ottenbreit-Leftwich (2010) noted that when teachers used technology to inform their teaching practices, change in their belief systems, pedagogy, content knowledge, instructional practices, and

resources often occurs. Researchers contend that change has been hampered due to a lack of knowledge, belief systems, low self-efficacy, lack of an instructor-centered focus, and institutional pressures to conform (Ertmer & Ottenbreit-Leftwich, 2010; Bain & McNaught, 2006). TPACK has enabled the sense-making of a complex web of relations that have existed when technology has been used to inform teaching and learning—gleaning its robustness from the interconnection of technology, pedagogy and content. These theoretical constructs occupied a pivotal role in the guidance of questions that were posed in the present study, research methods selected, collection of data, analyses, and recommendations rendered.

Researcher's role. An international conference was selected for the research study due to its timeliness, proximity to the study, global appeal and focus upon teaching and learning in higher education. Similar studies on learning analytics and instructors' technology use, portrayed in the literature review, have utilized annual conferences in their research endeavors.

In reference to my role as the researcher, I was unfamiliar with the director and board members of this society, and had never attended their annual meetings. This non-relationship allowed me to persist as unbiased surveyor. Access was facilitated through a structured meeting with the director; the director met with other board members, discussing the proposed study and data collection. Written permissions were granted by the society's board members and director. An application for research protocol was submitted and approved by the University of Nevada Las Vegas institutional review board. The researcher respected the rights, needs, values and desires of the respondents and abided by the specifications as required by the professional society. These specifications were noted under participant and site selection.

My background in learning analytics and academics in higher education guided my interest in exploring the study of instructors' usage of learning analytics. More specifically, I

conducted a pilot study on the use of learning analytics at the College of Southern Nevada in the Fall of 2014 and reported on the results at various in-service seminars at the college and at conference meetings during the spring of 2015. I brought certain biases to this study although efforts were made to ensure objectivity. These biases channeled my view and representation of the data.

Participant and site selection. The population consisted of those registered to attend the yearly meeting of an international society for the scholarship of teaching and learning conducted in Fall of 2016 in the Southwestern U.S. The rationale for data collection through a professional association was inspired by previous studies by Educause (Bichsel, 2012; Dahlstrom, 201l; Dahlstrom & Brooks, 2014; Educause, 2012), ensuring the inclusion of professionals in higher education. This organization hosts about 600 members with more than half (350) registered to attend their annual meeting. The conference has attracted higher educational professionals globally, with 66% registered from the U.S. and the remaining from other countries around the globe. This international society was chosen due to their emphasis on teaching and learning in higher education, availability and the annual meeting's close proximity to the study. After gaining approval to conduct the research, I contacted and worked with the director of the society to obtain a list of criterion-based participants. The selection of respondents consisted of a nonprobability sampling as it was self-selected and voluntary.

The researcher conducted a convenience sample, consisting of those who were registered and attended the conference, met the selection criteria, and were available to participate; a random sampling procedure was not used. The purpose of the survey research was to explore characteristics, extent of usage, attitudes, and behaviors of the population. The advantages of conducting a survey included the low-cost of the design, the speedy turnaround of data

collection, and the capacity to classify characteristics of the population from a smaller group (sample). The survey was cross-sectional—gathering data from one point in time (Creswell, 1994). Merriam (2009) suggested the selection of respondents should be representative of the population so that the researcher gleans more insight. Selection criteria focused on instructors (whether adjunct or full-time) that currently or have taught within the past five years in higher education (as learning analytics have gained popularity since 2011). Full-time information technology experts and administrators were excluded from the sampling process if they did not have teaching responsibilities. Within this population, participants could respond regardless of their academic department or type of institution of higher learning. This selection was necessary to ensure a reasonable sample size and a cross-analysis of all instructors in higher education in the U.S. and abroad.

Per the society director's instructions, a table was set-up at the annual meeting with a large sign overhead to attract potential respondents. The researcher was directed not to single out potential respondents while working at the table, rather to allow the instructors to initiate contact with the researcher. The sign listed the words: *PhD Candidate Requests Your Participation in a Survey*. After the conference attendee made contact, the researcher first polled potential respondents with a question: *Have you taught within higher education during the past five years?* If the attendee, answered *no*, then he/she was thanked for their consideration but informed that a requirement for participation was teaching responsibility during the previous five years. Thirty-six potential respondents did not meet the criteria of selection due to a lack of teaching experience; most of their jobs were administrative in nature. If the attendee answered *yes*, they were asked a second question: *Are you comfortable with questions regarding your teaching practice?* All of the potential respondents answered *yes* to this question. The

respondents were reminded that the survey was voluntary and they were at liberty to stop for any reason at any time. The potential respondents were given choices: (a) to complete a paper questionnaire at the table (see Appendix A); (b) take a survey, complete it later, and then return it to the researcher; (c) obtain a quick response code (QR code) printed on a paper that provided a link to the online survey; (d) submit their business card with their email address so that the survey could be distributed to them later; or (e) print their name and email address on a list for future completion of the survey. Some attendees were arbitrarily and casually informed of the survey between break-out sessions, during lunches, social hours, and specially scheduled peer and social activities. During these events, the researcher referred the instructors to the table located in the vendor section of the conference area. Per the request of the association, paper questionnaires were not distributed during scheduled sessions. A breakdown of the distribution and collection of instruments included: sixty-five completed paper questionnaires (out of a distribution of 91), dispersal of one-hundred QR codes, a gathering of eleven business cards, and listing of ten email addresses. After the cessation of the conference, the society emailed the Qualtrics survey URL to all members of the society. Instructors were encouraged to complete the survey if they had not completed one previously at the conference. These measures resulted in the completion of one-hundred and fourteen surveys.

Since this study also reflected upon phenomenological research, a question necessary to this research was: *Do the respondents have the experience that is essential* (Englander, 2012)? The researcher conducted a *judgment sample*, or *expert choice sample*, whereas the identification of four instructors (currently or previously using learning analytics in their teaching practices) were chosen for personal interviews. Conversations with instructors at the conference in reference to their extent and use of learning analytics in their practice, yielded two experts.

These two individuals were asked: *Would you feel comfortable sharing more in-depth information about your learning analytics' practice in an interview?* Both instructors agreed to participate in an interview; a time and location were set between conference sessions. To protect anonymity, each attendee was informed that the information gathered would not link his/her name or institutional affiliation to the research study. This purposeful sample was selected to reveal new information (and perhaps dispute former beliefs) that would prove vital for the construction of the experience (Englander, 2012). Since the conference only yielded two experts, a search for additional experts was undertaken. A snowball (respondent driven sampling) (Atkinson & Flint, 2001) research strategy was utilized to find suitable experts. This strategy has been used to locate concealed populations that are often isolated. It is a type of link-tracing whereas social networking is used to identify respondents (Atkinson & Flint, 2001). This method was introduced as snowballing by Goodman (1961); it was expanded upon and popularized by Heckathorn (1997) as respondent driven sampling—to access hidden populations that are difficult to sample due to small sizes and low response rates. This method, based upon Markov-chain theory and the theory of biased networks, has reduced the biases usually associated with chain-referral sampling methods. In this connection, a purposefully chosen sample of information technology administrators served as initial contacts at select institutions of higher learning in the Southwestern U.S. Ease of access determined the initial sample. These subjects were selected based upon their positions at their respective institutions of higher learning in online learning or curriculum design. This type of sampling (key informant) was used to overcome response biases by selecting knowledgeable subjects (Heckathorn, 1997). Via telephone communication, and after proper introduction, these subjects were asked the following question: *Do you know of an instructor at your institution of higher learning that is an expert on*

the use of learning analytics in their teaching practice? One of the institutions posted this question on one of their online chat boards, but no responses were collected. Of the fifteen subjects contacted, three offered the names of individuals that fulfilled the research criteria. Three were contacted either by email or by telephone. The potential respondents were informed of the significance and parameters of the research study. One of the experts chose not to participate in the study. One expert was chosen due to having experience with multiple learning management systems and their corresponding learning analytics. Another expert was purposefully selected due to her previous use of learning analytics, and subsequent discontinuation. All of the interviews involved note-taking—no recording devices were used. The notes were typed after the ending of each interview to maintain and ensure as much clarity and depth of information as possible. After the notes were typed, they were distributed to the interviewees. The interviewees conducted member checks of the information provided in the interview documents to clarify any ambiguities or forgotten or eclipsed content. No corrections were needed as the interviewees did not find any comments objectionable, lacking or out-of-context. The notes for two interviewees selected through the snowball sample were typed after the interview and emailed the following day to provide a member check of the information. No corrections or additions were indicated by the interviewees. The interview questions were located in Appendix B.

Instruments. A survey design was used to solicit information from those registered to attend the international conference on teaching and learning. The instrumentations used in the study included similar questions utilized in formerly published studies (Bichsel, 2012 & 2013; Dahlstrom, 2016; Dahlstrom & Brooks, 2014; Pomeroy, 2014). Creswell (2012) and Marshall and Rossman (2011) recommended the use of survey questions developed and validated in

preceding studies to take full advantage of credibility. Three studies were reflected upon, namely: Dahlstrom & Brooks, *Study of Faculty and Information Technology* (2014), Dahlstrom's *Inquiry on Faculty Use of Learning Analytics (*2016), and Bichsel's *ECAR Study* (2012). Simple procedures were adhered to in the construction of the questions. Definitions and examples were provided to better clarify the question at hand. The survey questions were simply, straight-forward, easy to answer, and thoughtfully designed to get trustworthy results. The first question in the survey reviewed the purpose of the research, the names of the researchers, and an invitation to participate. Confidentiality was addressed stating that the collection of identifying information would not be gathered. A telephone number was included. None of the respondents chose to call the researchers.

Survey Questions. Open-ended questions and questions with finite answer categories based upon ranking scales were utilized. Simple, non-leading and direct language was used in the construction of the survey. Questions were specifically designed and based upon the affordances and challenges located in the review of literature. The questions were clear, concise unbiased, and framed appropriately for ease of understanding. After the initial construction of the questions, experts were contacted for their review and feedback. Two experts in the field of educational technology and research reviewed the questions and answer categories, offering insight and guidance.

The first step in developing the questions was to organize and separate the affordances and the challenges. The 23 affordances were offered as answer categories in the following question: *How do you currently use learning analytics in the courses that you teach?* For each of the affordances listed, respondents used a ranking scale to denote their usage as: *never, don't know what it is, seldom, sometimes, often, most of the time*. A question was designed to

determine why instructors may have previously used analytics, but consequently discontinued use. This question, offered 25 possible answer choices. Instructors could select as many as they felt were applicable by marking the box. The close-ended questions permitted evaluation and analysis of factors enabling the data to be easily investigated and examined (Creswell, 2012). Open-ended questions were offered to allow the respondents to answer the questions freely—expressing their expectations, experiences, general perceptions, dispositions, attitudes, and conveying other elements of their lived teaching practice. These questions included the following:

- Which learning management system do you use at your place of employment?
- If you have used learning analytics, what challenges have you faced while using learning analytics in the courses you have taught?
- Are there any other areas not specified in the previous questions/s in which you are using learning analytics? If so, please explain.

The use of these open-ended questions helped to maximize credibility (Creswell, 2012). All of the questions were reviewed by the two experts. Suggestions were carefully explored resulting in minor modifications of the original questions. The experts were satisfied with the final survey questions and answer categories.

Respondent Characteristics. The survey posited questions about years of experience, rank, along with questions about their use of learning analytics within their educational environments, including experiences in research and scholarship. The following questions about professional demographics were addressed: (a) In what state and country do you work; (b) What is your gender; (c) How long have you worked in higher education; (d) Where do you work; (e)

what is your level of education; and (f) Which of the following best describes your academic rank during the current academic year?

Learning Management Systems. The survey explored the respondent's use of learning management systems. The following question was offered: *Which learning management system do you use at your place of employment?* The answer choices included a list of the most commonly used learning management systems along with two other options: (a) I don't know which learning management system is used at my place of employment, and (b) other, please specify (an answer category allowing the respondent to answer freely). The second question in reference to learning management systems targeted frequency of use. The question posited: *How often do you use this learning management system at your place of employment (on campus or elsewhere online) for the courses that you teach?* If the respondent answered *never*, display logic was used to end the survey and the instructor was thanked. If the respondent used the learning management system at least a few times each semester, display logic was used to direct them to the next question about their use of analytics within the learning management system.

Learning analytics. A group of five questions targeted the instructors' usage of learning analytics. The first question defined learning analytics and offered examples. The question was posited: *Do you use learning analytics within your learning management system for any of the courses you teach?* If the respondent marked *no*, display logic was used to end the survey and the instructor was thanked for their participation. If the respondent chose *yes*, they were directed to the following questions: (a) *How do you currently use learning analytics in the courses that you teach* [with twenty-three possible answer categories]; and (b) *Are there any other areas not specified in the previous questions/s in which you are using learning analytics? If so, please explain* [open-ended question]. Respondents choosing the answer category: *I previously used*

learning analytics but I don't use them anymore, were referred to the following question through display logic: *If you PREVIOUSLY used learning analytics, but you are NO LONGER using them, please tell us why by checking the box(es) below.* This question had twenty-five answer possibilities. The respondent could choose any or all of the answers that were applicable by checking a box. The final question was posited: *If you have used learning analytics, what challenges have you faced while using learning analytics in the course you have taught?* This was an open-ended question.

Interview questions. Four expert interviewees were selected and subsequent interviews were conducted in-person. Two of the participants were chosen through a convenience sample from the pool of attendees at the annual conference; two were chosen through a snowball research strategy. The questions reflected upon information derived from the literature review. More specifically, questions targeted their lived experience, including challenges and the value of use. The following questions were addressed:

1. Can you please describe as detailed as possible a special situation in which you have used learning analytics in your practice of teaching at your institution of higher learning;
2. How do you believe your use of learning analytics will change in your near future;
3. Do you believe your use of learning analytics helps students? Please explain;
4. What if any are the mitigating factors influencing your use of learning analytics; and
5. Do you believe the use of analytic tools in your teaching practice is worthwhile? Please explain.

Each interviewee was asked these five questions in succession; the responses provided more in-depth information so that a thicker description of the practitioners' experience of learning analytics was explored. Data analyses were conducted simultaneously with the data collection

(Creswell, 1994). Follow-up questions based upon the interviewees responses were used at the discretion of the interviewer for supplementation. All four experts completed a paper questionnaire of the survey and their data was included in the survey findings as well. Information gathered from the interviewees' surveys was reviewed by the investigator and discussed more thoroughly during the interview process.

Data Collection Procedures

Attendees that visited the table at the conference were initially surveyed to determine if they held present or previous teaching positions as an instructor at an institutions of higher learning in the past five years. Data was collected at the conference via paper surveys; other respondents completed the survey online. After the total number of respondents were tallied, there existed an insufficiency of responses. Consequently, members of the society were contacted via email for participation in the study after the cessation of the annual meeting.

Two of the expert interviews were conducted between scheduled conference sessions at the convenience of the respondents. The other two experts were selected through a snowball sampling technique and interviews were conducted after the conclusion of the conference.

Data Analyses

To explore factors relating to the adoption, nature, and extent of use of learning analytic tools, data from the respondents' surveys and interviews were analyzed separately. The goals of data analyses were (a) the exploration of instructors' usage of learning management systems,(b) an examination of instructors' usage of learning analytics, (c) a deeper understanding of the phenomenon from lived experiences, and (d) challenges to adoption, implementation and continued use. Descriptive analyses were conducted on the responses from the survey items with finite answer categories through Qualtrics.

This investigation targeted the nature and extent of learning analytics from an instructors' perspective; the data analyses helped to formulate a picture of current analytics practices by instructors in higher education. It was essential to present results obtained from each variable in the form of frequencies and percentages. Distributions of age, gender, professional ranks, and institution types were assessed illuminating characteristics of the instructors participating in the study. Beyond these, questions specifically targeted the instructors' usage of analytics exploring the following:(a) regularities, (b) inconsistencies, and (c) a comprehensive meaning of instructors' practices.

Notes were handwritten during the expert interviews and then typed within a few hours to maintain integrity. Conventional content analysis with Atlas TI was utilized to reduce data, sort and identify meaningful data chunk. Themes emerged; these were explored and coded—rendering a more in-depth analysis of the phenomenon and the developing story (Creswell, 2012). The primary strategy to ensure validity was the provision of a thick rich detailed description of the lived experiences of the phenomenon.

Ethical Procedures

Permission to interview participants for this study was received from the director of the society's annual conference and board members (see Appendix C). Measures to ensure privacy of the participants of the study were undertaken to ensure trustworthiness. Pseudonyms were used to protect the identities of the interviewees. All documents relating to this study have been housed in a secure environment; any pertinent information in reference to complete (first and last) names or institutional affiliation will not be made public. Member checks were afforded to the experts so that the participants had the opportunity to review the findings. Ethical concerns were mitigated using consent forms and approval by the institutional research board.

Conclusion

Many learning management systems have provided easy-to-visualize and interpretable learning analytics allowing instructors the ability to explore students' engagement and participation more in-depth; this may in turn affect student learning and teaching practice. The review of literature did not reflect studies focusing upon instructors' lived experiences. This chapter presented a two-phased research approach—a dominant-less dominant design—as proposed by Creswell (1994). This study was designed to address the gap in literature between the promises presented through research studies on the affordances of learning analytics and actual use by instructors. The analyses of the data have been presented in Chapter 4.

Chapter 4

Analyses of the Data

Chapter 4 includes the analyses of data; it has been organized into major sections. The first section included the examination of the respondents through the analyses of descriptive variables. The second section involved the respondents' use of learning management systems. The final section encompassed a thoughtful reflection on the three research questions with emphasis first on the survey findings and then secondly from analyses of expert interviews. The following research questions were addressed:

RQ1: How do instructors at institutions of higher learning explore learning analytics to reflect upon their teaching practices, curriculum, or pedagogy?

RQ2: How do instructors at institutions of higher learning explore learning analytics to reflect upon student learning and outcomes?

RQ3: What are the perceived key challenges to the adoption or use of learning analytics by instructors at institutions of higher learning?

Respondents

The survey instrument was available to 350 attendees of an international conference on teaching and learning in higher education held during the Fall of 2016. This conference was chosen due to its global attraction, emphasis on teaching and learning in higher education, availability and geographical location to the study. Of the 350 potential attendees at the conference, with approximately 600 members in the society, 114 instructors completed the survey. Of these, 69 respondents completed a paper questionnaire while 45 completed the survey online. The data from the paper questionnaires were manually input into Qualtrics and double checked for accuracy. Of those that completed the survey online, some were given a QR

code that directed them to the webpage while the remaining were given a URL through email distribution either directly from the society or from a harvesting of emails at the conference site. The response rate from this survey was 19% (based upon the total membership since a request to participate in the survey was emailed after the annual meeting concluded).

The design of this research study was exploratory in nature. The goal was to provide a descriptive picture of learning analytics usage by instructors in higher education. The following variables were examined to provide a professional description of responding instructors: (a) gender, (b) geographical location, (c) years of service, (d) classification, and (e) type of institution of higher learning.

Location. Most of the respondents were from the U.S. (86%). The following countries were also represented in this study, including Taiwan, Australia, Vietnam, South Africa, China, and Canada (see Figure 5). The lower response rate from countries outside of the U.S. was most likely due to the annual conference being held in the Southwestern U.S.

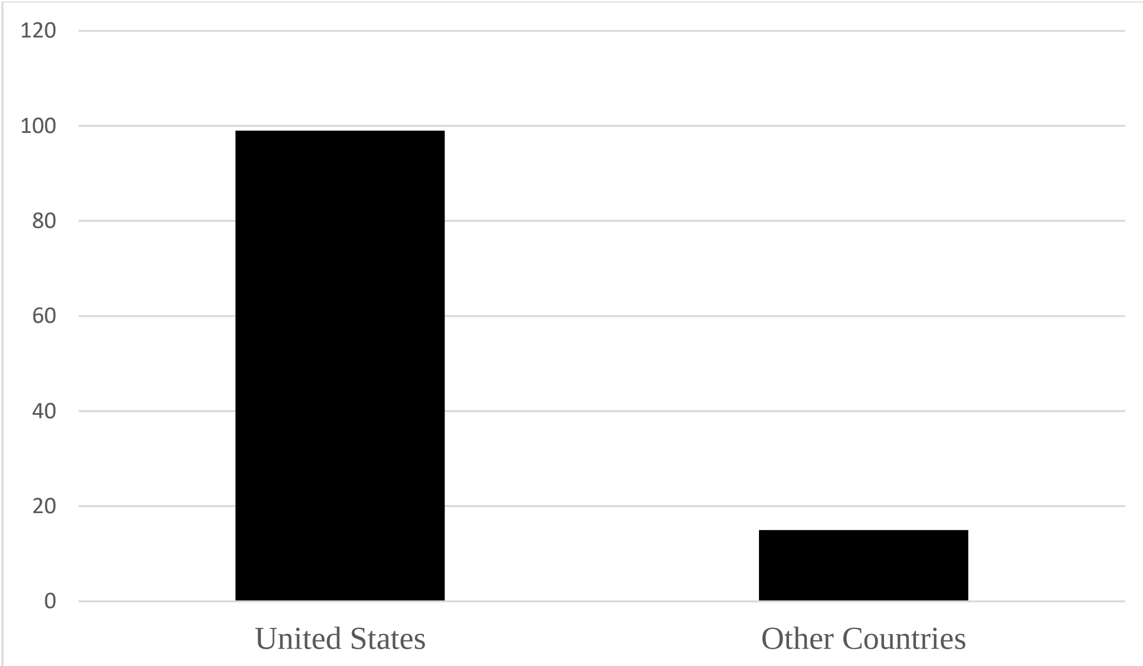

Figure 5. Respondents by Country. Respondents in this study were primarily from the U.S.

More survey responses were from Canada than other countries outside of the U.S.—most likely due to the proximity to the conference. Responses were gathered from 39 differing states—with southern states closest to the conference offering the most representation.

Gender. Of the respondents, females were more likely to complete the survey (56%) than males. Four respondents did not choose to report their gender and one utilized the classification of *other* (see Figure 6).

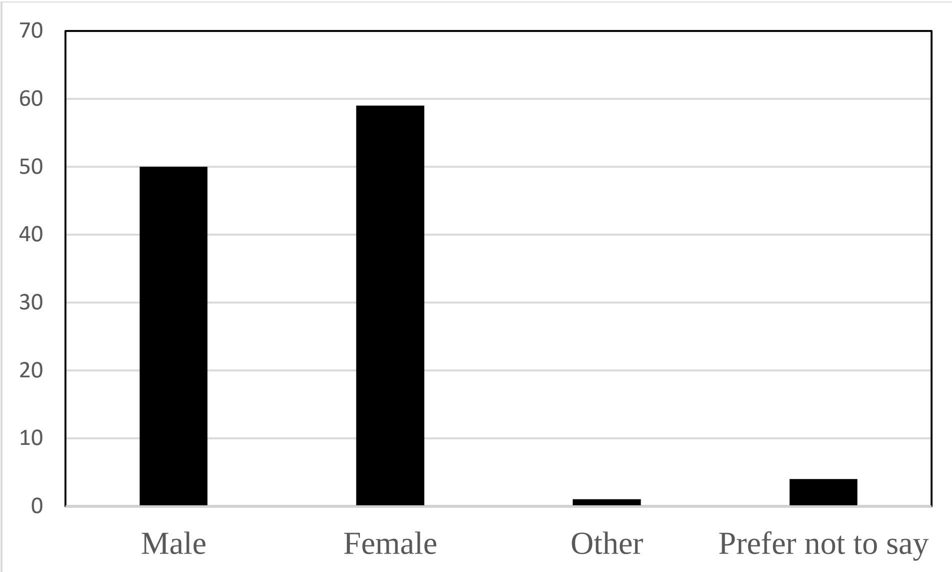

Figure 6. Respondents by Gender. Slightly more females answered the survey than males.

Years of service. Respondents were polled on their years of service in higher education. New instructors and those that had the highest years of service were the least represented in this survey. Instructors with less than five years of service were more likely to complete the survey, closely followed by instructors with 11 - 20 years of service. First year instructors were least represented in this survey and may be attributable to a lack of professional development funding due to a shorter term of service (see Table 4). Training, professional development and incentives were explored further in this study.

Table 4

Respondents' Years of Service

Years of service	Total	%
First year Instructor	10	8.7
1-5 years	26	22.8
6-10 years	27	23.6
11-20 years	31	27.2
More than 20 years	20	17.5
n = 114	114	

Type of Institution of higher education. Fully online institutions of learning were least represented in this survey (4%) while the majority of respondents were employed by universities with or without masters and doctorate degree programs. Approximately one-third of the respondents worked for a community college. One respondent did not list a type of institution (see Table 5).

Table 5

Type of Institution

Type of Institution	Frequency	%
None reported	1	< 1
Community college	33	29
4-year college	16	14
University not including masters or doctorate programs	12	10.5
University including masters or doctorate programs	48	42
Fully Online	4	3.5
n = 114	114	

Level of education. The majority of the respondents reported either a master's degree or a doctorate (39% and 53% respectively). Approximately eight percent of the respondents reported receiving less than a bachelor's degree (see Figure 7). Reflecting upon discussions with attendees at the conference, some information technology experts reported teaching courses in applied and technical sciences without a formal degree. Explanations were given that certifications in their respective fields served credentialing purposes. This may account for some of the instances where the instructor had earned less than a bachelor's degree.

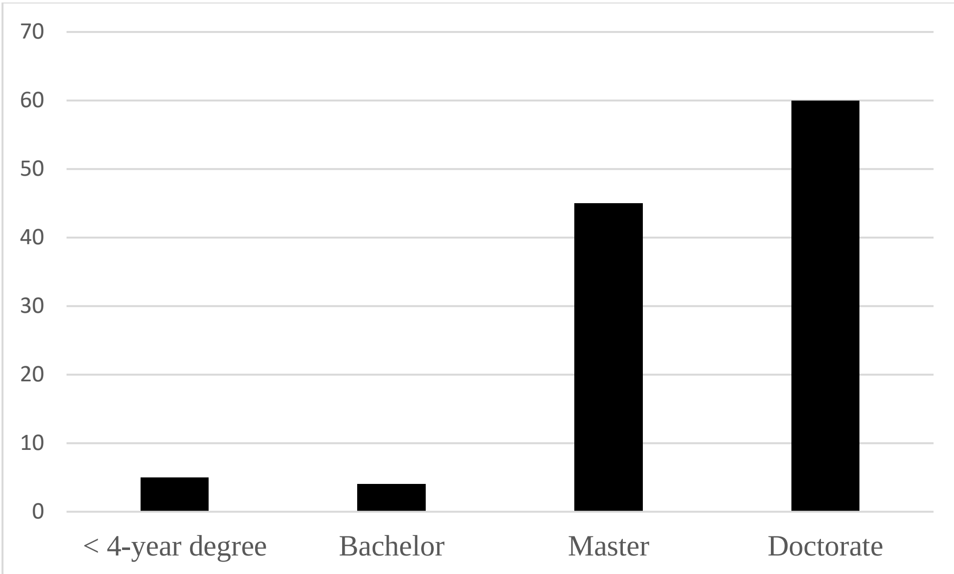

Figure 7. Respondents' level of education. The majority of the respondents had acquired at least a master's degree.

Academic rank. A greater number of the respondents reported their academic rank as professor (54%) rather than instructor (42%). The remainder of the respondents did not report an academic ranking (see Figure 8).

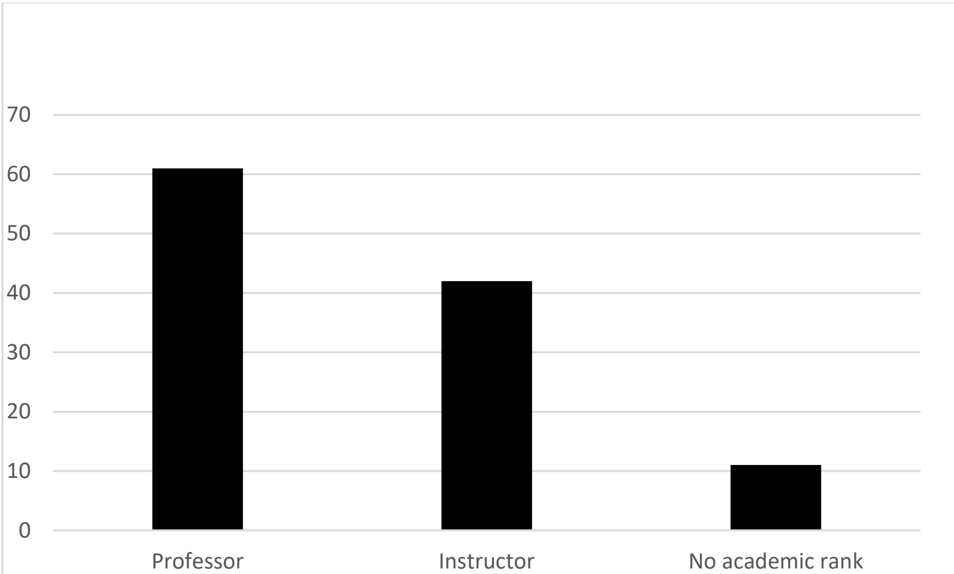

Figure 8. Respondents' Academic Rank. Most respondents were classified as a professor in this study, followed by instructors.

Learning management systems. Consistent with the literature review, the majority of the respondents (39.5%) reported Blackboard as their learning management system at their institution of higher learning. Following Blackboard—Canvas and Moodle were most often used. The proprietary learning management systems by Pearson eCollege were reported by slightly more than six percent of the respondents. Approximately eight percent of the respondents did not know which learning management system was used at their place of employment. Five respondents chose the *other* category. One of these respondents reported using Google Classroom while others developed their own online course. Two respondents reported that a learning management system was not advantageous or applicable to their teaching responsibilities (see Table 4).

Table 4

Type of Learning Management System

Type of Learning Management System	Frequency	%
Blackboard	45	39.47
Canvas	27	23.68
Moodle	12	10.53
I don't know which LMS is offered at my institution	9	7.89
Desire to Learn (D2L)	7	6.14
Pearson eCollege	7	6.14
Sakai	1	.88
Other	6	5.26
Jenzabar e-Racer	0	0
n = 114	114	

When respondents were asked about their usage of learning management systems, the majority (60%) reported using them at least weekly. Ten percent of the respondents stated that they never use a learning management—and equally—ten percent noted using it only a few times each semester. Over 90% of the respondents reported at least some usage of the learning management system during the semester (see Table 5).

Table 5

Frequency of Learning Management Usage

Frequency	Number of Respondents	%
Daily	39	34
Weekly	30	26
Monthly	23	20
A few times each semester	11	10
Never	11	10
n = 114	114	

Research Questions

RQ1: How do instructors at institutions of higher learning explore learning analytics to reflect upon their teaching practices, curriculum, or pedagogy?

The respondents were presented with a definition of learning analytics as stated by Bichsel (2012), referring to the "…use of data, statistical analysis, and explanatory and predictive models to gain insights and act on complex issues" (p. 6). Examples were offered to illustrate more common affordances of learning analytics. These included: (a) determining the number of page views by students, (b) the average score on an exam, (c) amount of log-ins, and (d) the number of posts on a discussion board. The respondents were surveyed to determine whether or not they have used learning analytics in any capacity at their institution of higher learning. The greater number of respondents (64%) reported never using learning analytics while 11 percent reported previous—but not current use. Therefore, three-fourths of the respondents have either never used learning analytics or previously used them and consequently stopped (see Table 6).

Table 6

Usage of Learning Analytics

Use of Learning Analytics	Frequency	%
Yes, I currently use learning analytics	37	32.46
No, I have never used learning analytics	64	56.14
I previously used learning analytics but I don't use them anymore	13	11.40
n = 114	114	

Teaching practice, curriculum and pedagogy, non-usage. Respondents were polled about their use of learning analytics in their teaching practice (Table 7). Twenty-three affordances of learning analytics were offered. Respondents could choose from answer categories including *never*, *seldom*, *sometimes*, *often* and *most of the time*. A reflection on how learning analytics *were not used,* was assessed. From the data, it would appear that instructors used learning analytics pro-actively in a supervisory means as a watchful guardian rather than using the analytics as a watchdog for unethical conduct. Specifically, 60% of the respondents did not use learning analytics for instructional management—dropping students for non-participation. Over half of the respondents did not use analytics to detect cheating. Slightly less than half reported not using analytics to determine students' usage and non-usage. The literature review suggested that learning analytics have afforded, (a) a personalized learning experience, (b) a means to target at-risk students, (c) a springboard for intervention, (d) a means for improving retention, and (e) as a target for current research purposes. The respondents, however, didn't necessarily view these in the same manner. Over a third of the respondents did not use

analytics to provide a personalized student learning experience nor early-alert system. Approximately half of the respondents did not use analytics to improve retention in their courses. Over half of the respondents did not use analytics for research purposes.

Table 7

Teaching Practice, Non-use

Question	%	Frequency
Frozen Data (snapshots or dashboard(d)	38.89	14
System generated data (from clicks, swipes or sensors)	29.73	11
Enhance student learning	22.86	8
To refine my course	28.57	10
To provide a personalized student learning experience	40.00	14
To refine exam questions	37.14	13
To determine time needed for assessments or assignments	37.14	13
To monitor discussions and or the number of posts	22.22	8
To monitor log-ins by students	19.44	7
To detect student cheating	54.29	19
To monitor students' time spent in the course	33.33	12
As an early-alert system to determine students at risk	36.11	13
To manage student engagement in the course	23.53	8
To assess patterns of student learning management usage and non-usage periods	43.24	16
To assess mean/standard deviation of students' test scores	28.57	10
For instructional management - dropping students for non-participation	60.00	21
For instructional management - to determine student progression within the course	14.29	5
To provide intervention	25.71	9
Measure learning outcomes and goals	28.57	10
Analyze trends	35.29	12
To reflect upon and enhance my own teaching practice	34.29	12
To improve retention in my courses	48.57	17
For research purposes	54.29	19

Teaching practice, curriculum and pedagogy use. Respondents were polled about their use of learning analytics in their current teaching practice. Twenty-three affordances of learning analytics were offered as possible answers. Respondents could choose from answer categories including *never*, *seldom*, *sometimes*, *often* and *most of the time*. A reflection on how learning analytics *were used*, was assessed. Table 8 presents the findings from those responses marked *seldom*, *sometimes*, *often* and *most of the time*. The data reflected that when learning analytics were used by instructors, their usage was low reflecting *seldom* or *sometimes* usage. The lowest reported learning analytics usages were categorized as being utilized *most of the time*.

Table 8

Use of Learning Analytics

Question	Seldom	Sometimes	Often	Most of the Time	Total
Frozen Data (snapshots or dashboard)	7	8	3	1	19
System generated data	10	5	5	3	23
Enhance student learning	2	13	4	7	26
To refine my course	4	11	8	2	25
Personalized student learning experience	5	7	4	4	20
To refine exam questions	2	12	5	3	22
To determine time needed for assessments	4	11	6	1	21
To monitor discussions and or the number of posts	4	9	3	12	28
To monitor log-ins by students	6	10	6	7	29
To detect student cheating	8	4	3	0	15
To monitor students' time spent in the course	6	10	7	1	24
As an early-alert system	5	4	6	8	23
To manage student engagement in the course	6	8	6	6	26
To assess patterns of usage and non-usage periods	5	8	6	1	20
To assess mean/standard deviation test scores	5	8	10	2	25
Dropping students for non-participation	3	6	4	1	14
To determine progression within the course	8	15	2	5	20
To provide intervention	10	8	4	3	25
Measure learning outcomes and goals	2	10	10	2	24
Analyze trends	5	7	8	2	22
Enhance my own teaching practice	4	4	11	4	23
To improve retention in my courses	1	8	7	2	18
For research purposes	5	6	4	0	15
Total number of reported usages of learning analytics	117	192	132	77	

With a sample size of 114, the usage of learning analytics tools was quite low, with less than 25% percent of respondents reporting at least occasional use (*seldom*). Few respondents reported using learning analytics *most of the time*. Of those respondents using analytics *most of the time*, their use centered around enhancing student learning, monitoring of discussions and or the number of posts, monitoring logins by students, as an early-alert system to determine students at risk, and for instructional management to determine student progression within the course.

Overall, when learning analytics were used, it was often positive or supervisory in nature. The affordances included: (a) enhancing student learning. (b) monitoring of discussions and or the number of posts, (c) checking log-ins by students, (d) managing student engagement in the course, (e) providing intervention. and (f) measuring learning outcomes and goals. In reference to curriculum—approximately 20% of the respondents noted that learning analytics were used to enhance their own teaching practice, for course redesign, to provide a personalized student learning experience, and for the refinement of exam questions. Respondents were given an option to add additional information on their usage via an open-ended question. This question inquired: *Are there any other areas not specified in the previous questions/ in which you are using learning analytics? If so, please explain.* This question allowed for a more thorough discussion of instructors' practice not bounded by set answer categories. While most of the responses were student centered, two responses were supervisory in nature and specifically targeted the performance of instructors. In this connection, one respondent added that learning analytics were used outside of student learning in a supervisory manner to compare the work of instructors. Insomuch, analytics were used to compare statistics on students' attendance, mean scores on tests, and achievement of outcomes amongst and between instructors. Another response included the scheduling of *superior instructors* over others. These might suggest that

analytics were used either as a watchful guardian or a watchdog, given the intent of their use. Another respondent added that learning analytics were used to compare their own students' work with others globally. One respondent acknowledged their institution's migration to Canvas during the current semester and that he/she had not figured out what is available yet—apart from assignment statistics. Another respondent reported using analytics to determine those students not achieving minimal requirements.

RQ2: How do instructors at institutions of higher learning explore learning analytics to reflect upon student learning and outcomes?

Six questions on the survey targeted learning outcomes. Respondents were surveyed to determine if they used learning analytics to (a) enhance student learning, (b) provide a personalized student learning experience, (c) manage student engagement in the course, (d) determine student progression, (e) measure learning outcomes and goals, and (f) improve retention. Less than 15% of the respondents reported using learning analytics to inform learning outcomes and goals. More instructors failed to use learning analytics at all—rather than those that chose to use them *most of the time*. Overall, instructors that have used learning analytics, tended to use them at least on an occasional (seldom) basis (see Table 9).

One question specifically addressed learning outcomes and goals within the survey while the other five questions were more indirect. When asked directly about the measurement of learning outcomes and goals, more instructors reported not using learning analytics (n = 10) rather than using them *most of the time* (n = 2). With the total sample size of 114, and only two respondents using analytics *most of the time*, the utilization of learning analytics to measure learning outcomes and goals were reportedly very low. When learning analytics were used *most of the time* by instructors, the use centered around enhancing student learning, managing student

engagement in the course and for instructional management to determine student progression within the course (see Table 9).

Table 9

Learning Outcomes

Question	Never	Seldom	Sometimes	Often	Most of the Time
Measure learning outcomes and goals	10	2	10	10	2
To improve retention in my courses	17	1	8	7	2
To provide a personalized student learning experience	14	5	7	4	4
Enhance student learning	8	2	13	4	7
To manage student engagement in the course	8	6	8	6	6
To determine student progression within the course	5	8	15	2	5

RQ3: What are the perceived key challenges to the adoption or use of learning analytics by instructors at institutions of higher learning?

Respondents were surveyed to determine their usage of learning analytics within their learning management system. Over half of the respondents noted that they had never used learning analytics while 11% admitted previously using them—but discontinued use. Therefore, two-thirds of the respondents were presently not using analytics (see Table 10).

Table 10

Current use of Learning Outcomes

Use of Learning Analytics	%	Frequency
Yes, I currently use learning analytics	32.46	37
No, I have never used learning analytics	56.14	64
I previously used learning analytics but I don't use them anymore	11.40	13
n = 114	100	114

One question on the survey was posed only for those respondents that stated that they had previously used learning analytics and consequently discontinued use. This question was directed at their reasoning behind their change in use: *If you PREVIOUSLY used learning analytics, but you are NO LONGER using them, please tell us why by checking the box(es) below.* A finite set of 25 answer categories were presented. An analysis of the answers to this question have been used to determine key challenges to the continued application of learning analytics by instructors. The most frequently cited reasons behind the discontinuation of learning analytics included a lack of worth and diversion from their teaching responsibilities. Other reasons cited more often included: (a) a lack of professional development or incentives to use learning analytics, (b) insufficient training on how to use analytics, (c) deficient evidence that learning analytics altered their method of teaching, and (d) learning analytics not being a part of their institution’s culture (see Table 11).

Table 11

Change in Learning Analytics Use

Question	Frequency
I didn't think it was worth investing my time nor talent.	12
My supervisor/college/university encouraged the use of learning analytics but since then I discontinued using them.	0
My learning management system doesn't offer learning analytics.	0
I don't use a learning management system with any of my courses.	2
I don't know how to use learning analytics.	3
I have never received training on the use of learning analytics.	6
My college/university doesn't offer campus assistance for learning analytics.	4
My college/university doesn't offer professional development incentives	7
I do not believe learning analytics altered my method of teaching.	7
I do not believe learning analytics would enhance student learning.	1
I do not believe the statistics in learning analytics are accurate.	0
Privacy issues	3
Learning analytics are too complicated.	1
I don't have the time to use learning analytics.	2
It is too difficult to learn analytics.	1
My colleague(s) used learning analytics and didn't find them to be useful.	0
It is not a part of my institution's culture.	7
It diverts time from my current research.	2
It diverts time from my teaching.	8
It is an imposition.	2
There is no relative advantage	2
There are no incentives for me to use them.	5
I am no longer teaching	1
I do not have the pedagogical expertise to make meaningful use of learning analytics.	0

Respondents were offered an open-ended question on the survey to explore any challenges they might have experienced with their use of learning analytics. This was the most frequently answered open-ended question within the survey. This question inquired: *If you have used learning analytics, what challenges have you faced while using learning analytics in the courses you have taught?* The responses provided a more in-depth exploration into the challenges of using learning analytics free from confined answer categories. Organization of the data began with reading and reviewing the respondents' answers. The data were organized and sorted. Common words and themes were grouped together. Codes were derived from the commonalities and served as a means to label, compile and shape the data into meaningful chunks. The data were summarized and synthesized linking similarities and differences. Coding and analysis were intertwined; it yielded three significant themes. These themes involved: (a) lack of time to learn or use the analytics, (b) problems with the learning management system and the analytics packages, and (c) insufficient incentives and or professional development opportunities. These themes advanced a story about the challenges inherent in current practice of learning analytics in higher education.

Lack of time. Lack of time to spend on learning the intricacies of learning analytics and the time needed to fully use these tools emerged as a theme. Time was cited as the most significant challenge to implementation and continued usage. One instructor reported that the time spent to gather information and then finding questionable correlations between analytics and students' learning and behaviors were frustrating. Another respondent added that "I have too many students to focus independently on a particular students' achievement or lack thereof."

Other respondents noted the association between time spent and lack of rewards. One respondent offered, “Giving up professional time should be traded equally” while another respondent concluded, “(Learning Analytics) Lengthens the course of my day without sufficient rewards for time well spent.” Lack of time to review, interpret and make the data actionable was cited by several respondents. A respondent added, “They [learning analytics] are often an afterthought, and I need to spend more time with them.”

Problems with learning analytics. Another theme that emerged from the data included problems inherent with the learning management system and the accompanying analytics package. Even though the responses in this theme were fewer, the tone appeared to be more impassioned in reference to the learning analytics. One respondent insisted,

> Sometimes the application of arcane analysis is a mathematical monster and ultimately provides insufficient information in a given class in a timely and useful manner. A general observation, a snapshot, if you will, can provide an instant picture of the health of the class and participants. When set up for grade performances across the class a picture will evolve that something is amiss. It MAY be the learning activity or the materials, or the presentation. On the other hand, in some cases, the material may be missed by the students because it is too advanced for their level of accomplishment. In any event, it affords the opportunity to adjust and re-target according to the evident obstacle. When done with quick temporal response, immediate adjustments or explanations can be delivered.

Another respondent presented their frustrations with the usability of the analytics. The persistence and insistence of their administration to push the use of analytics was viewed as quite

confusing since the information gathered was not being used. Additionally, when information was gathered, it was not actionable. Reflecting these concerns, a respondent conveyed:

> The system is opaque and not intuitive. It is also very pushy. The design tells you what learning analytics you SHOULD care about, and buries the ones you might ACTUALLY care about. Example: there is an attendance function, but you can't see the pattern of attendance for an individual student, only the number of absences. So you can't distinguish a student who regularly misses a class every two weeks from a student who has suddenly stopped coming. And there are too many options. The problem is that the administrators who are pushing these systems don't themselves actually use them.

This response also portrayed issues in the culture of the institution; a lack of institutional support was also conveyed by others. One respondent added, "Just not something we do at my university; I am capable of teaching without analytics."

Respondents also commented on their use of analytics within their institution's learning management system. References were made about Blackboard and Canvas. These two were discussed earlier in the findings as the two most frequently used learning management in the present study. Some of the frustrations reflected not only disenchantment with the system, but with the analytics packages. One respondent added,

> In Canvas LMS, (1) not all analytics are downloadable into Excel for further analysis; (2) some things I would like to track, such as instructor/student communication, do not provide enough detail; and (3) Canvas does not update reporting often enough, meaning admin reports do not correspond with Gradebooks in real time.

Comments were also offered by respondents noting their pleasure with their learning management system. Inn reference to Canvas, one respondent declared:

> I don't have any challenges. I believe our LMS is fantastic (Canvas) I've used others and it is much better in every way.

In reference to Blackboard (often referred to as Webcampus), issues with ease of use and the meaningfulness of the analytics were reported. In this manner, one respondent added,

> I believe that online activities analysis should be easier and more meaningful. I did not see other tools [that] are meaningful for face to face courses.

Another respondent added that analytics provided disaggregated data making it difficult to differentiate between quantity and quality. Also, addressing issues with students' scores within a course shell in Blackboard, a respondent affirmed,

> I frequently use the analytics packages in Blackboard. The greatest challenge is that my university does not allow me to delete a student's account from Bb even after they've stopped attending; their low scores are still averaged into the course's statistics. The other challenge is that not all faculty believe in the utility of statistics.

Lack of professional development, training or incentives. The third theme emerging from the data addressed challenges due to a lack of professional development opportunities afforded by and through their institution. More specifically, insufficient training and inadequate (or no) incentives were addressed. One respondent proclaimed, "I have never received training nor professional development opportunities for learning analytics; my college doesn't offer assistance for its use." Another respondent surmised that the institution did not provide any incentives; therefore, usage was not warranted.

Expert Interviews

Interviews were utilized as a means to gain a thicker description of learning analytics usage by practitioners to include the realm of lived experiences for this exploratory study. Four expert users of learning analytics in teaching practice were selected and interviewed for this study. Each of the experts signed an informed consent for this study. They were encouraged to give only the information that they felt comfortable to share. The interview stressed the interviewee's definition of the situation, encouraging them to structure their lived experiences. The interviewees introduced to a considerable extent that which he/she considered to be relevant. Each interview was targeted for one hour in duration but three of the four interviews lasted over two hours due to follow-up questions that added depth to the topic at hand. Participation in the study was voluntary; refusal to participate could happen at any point of the interview without prejudice. Each of the interviewees were given a pseudonym (Jack, Jason, Jackie, and Marianne).

Jack held a master's degree and has taught at a community college. His field of expertise has been in the natural sciences. Working full-time and with over ten years of teaching experience, he used the analytics provided in Canvas. He has taught both campus and online courses. He has used analytics extensively in all of his courses during the past five years.

Jason held a master's degree and has taught natural sciences at a university for five years. Jason used a Pearson proprietary learning management system rather than his institution's Blackboard (due to its utility and availability of analytics that provided a comparison of his students over others nationwide). He has also used clickers in the classroom to obtain instant analytics on students' learning. Jason has taught online, campus and dual-enrollment courses.

Jackie has earned two master's degrees, choosing to teach in only one of her fields of expertise (performing arts). She has taught at a community college for five years. Prior to receiving a full-time position, she worked at the same college as an adjunct in the same field for three years. As a full-time instructor, Jackie was an advocate for the use of analytics. With increased administrative responsibilities, Jackie's full-time teaching load was decreased to only two classes each semester during the past year. An admitted late adopter of computers and analytics in her teaching practice, she consequently discontinued use of analytics due to issues and specific circumstances she had experienced. She offered a differing perspective on the use of analytics due to her educational background, adjunct and full-time teaching positions, and administrative responsibilities.

Marianne held a doctorate degree and has worked at a community college full-time and at a university as an adjunct. She was a relatively new instructor with two years of teaching experience. Marianne had the most extensive experience (of the four experts) with analytics, reporting usage with Canvas, a learning management system designed specifically for her institution, and two proprietary learning management systems through book companies. Her background and work experience in the business field, yielded a deeper knowledge of statistics as well as analytics. She was a strong advocate for the use of analytics but also acknowledged the challenges inherent in implementation and continued use.

Analysis of Expert Interviews

The thoughtful review of literature helped to establish a picture of learning analytics—acknowledging the affordances and addressing the rhetoric. The questions posed to the interviewees were framed to encourage a nuanced exploration of the topic while focusing upon perceptions, change theory, and personal experience with learning analytics. The major topics of

actual practice, change, student intervention, and challenges were explored. The questions included:

1. Can you please describe as detailed as possible a special situation in which you have use learning analytics in your practice of teaching at your institution of higher learning;
2. How do you believe your use of learning analytics will change in your near future;
3. Do you believe your use of learning analytics helps students? Please explain;
4. What if any are the mitigating factors influencing your use of learning analytics; and
5. Do you believe the use of analytic tools in your teaching practice is worthwhile? Please explain.

The open-ended questions were offered in a sequence. Specific follow-up questions were not prearranged but were constructed during the interview process—based upon previous responses—to obtain a richer description of the phenomenon.

Notes were handwritten during the interviews and were typed immediately afterwards. The first step in the analysis was to read the typed notes from beginning to end. Analysis was made utilizing Atlas.Ti. Codes were used to serve as a label to compile and organize the data. The pre-set codes included practice, change, intervention and challenges; these were derived from the conceptual framework, research questions, and review of literature. The transcripts from the interview were re-read, dissected, organized, and recoded. Emergent codes developed from the sorting, coding and analysis. Word repetitions were examined and connected with lines and explanations. Word frequencies generated a list of unique words that were often cited during the interviews. These key words and excerpts from the interviews were recoded based upon the refined coding scheme denoting themes. Three themes emerged from the data, including: (a) efficient and effective use of time spent teaching in the classroom, (b) challenges of using

learning analytics in practice, and (c) monitoring and comparing students' progress. Sub-themes emerged within each of the three prominent themes (see Figure 9).

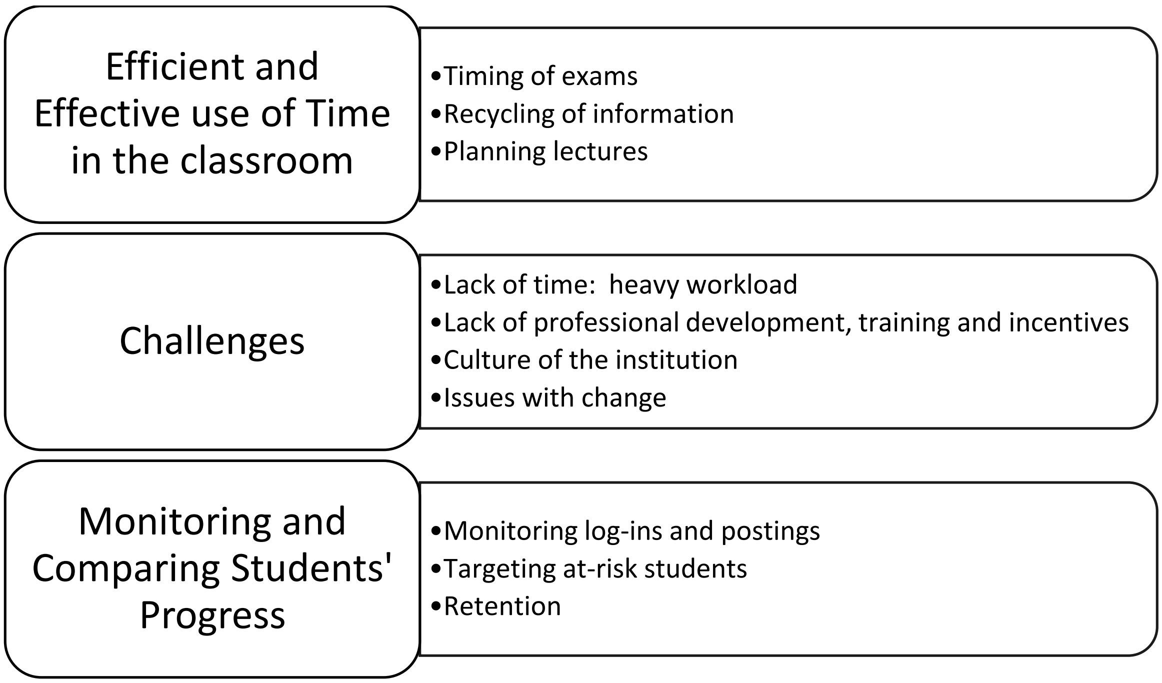

Figure 9. Themes Emerging from the Experts' Interviews. Three major themes with subthemes emerged from the data.

Efficient and effective use of time in the classroom. All four of the interviewees believed learning analytics were useful in the organization and efficient use of classroom time. Although this affordance was noted and prominent, all four experts commented on the challenges connected with heavy workloads and subsequent lack of time they have experienced with learning and using analytics. These challenges were addressed separately under the topic of *challenges of using learning analytics*.

Jason, has chosen to use a Pearson proprietary learning management system rather than his institution's Blackboard (due to its utility and availability of analytics providing a

comparison of his students with others nationwide). Jason actively used analytics inside and outside of the classroom on a daily basis. Accordingly, Jason declared,

> You can see how they (students) did on homework by viewing a panel. I can then tailor our next lecture based on how they did on homework. I can receive feedback in the classroom through Pearson Clickers, but there is an extra cost on top of what they (the students) are charged for student use of the LMS.

Furthermore, Jason expressed the affordance of more efficiently using classroom time. He discussed the importance of scheduling activities, lectures and exams to maximize learning within the classroom setting. He used analytics to determine time needed for in-class work. In this manner, analytics were used to gauge the time needed for students' completion of assessments and assignments. Furthermore, analytics were used to investigate trends (such as the popularity of learning activities with students) as well as to provide a reflection upon her own teaching practice.

Marianne's experience and enthusiasm with analytics was similar to Jason's. She proclaimed, "I spend time in class more efficiently and effectively." Marianne, even though she has worked in higher education only two years, discussed her extensive use of learning analytics including: (a) course analytics in Canvas, (b) an institutionally built and mandated proprietary learning management system, (c) Learn Smart, and (d) Dynamic Study. When using learning analytics, she noted that she was often surprised when the analytics portrayed that the students didn't *get* the concept. She indicated that with Learn Smart, students were given multiple choice questions (through a quiz) and then the results were tallied in an automated report. This report indicated the questions missed most often. Any concepts that required revisiting were referred to the *parking lot*. Any concepts that would be advantageous to be recycled or discussed more in-

depth—automatically went into the *parking lot* as an agenda item during the next lecture. She expressed her preference for Learn Smart due to its intuitive nature and the rendering of reports. She has also used Dynamic Study but preferred the features and analytics in Learn Smart. Even though she was enthusiastic about the affordances of learning analytics, Marianne affirmed, “To keep kids in the class, it takes teachers willing to go the extra mile.” Making a well-defined evaluation, Marianne proclaimed, “Analytics are the fireworks; I have to do the rest.”

Jack affirmed that time spent inside and outside of the classroom could be monitored more thoroughly through learning analytics. He used *quiz statistics* built into Canvas to monitor and gauge students’ knowledge of the topic at hand. When the mean score of the quiz dropped below 70 points, he automatically used the next lecture period to recycle information that was most often missed. If students’ mean score was greater than 70, he then progressed to new topics during the next lecture. Beyond this, quiz statistics were utilized to determine the average time needed for students to complete an assignment or quiz. Jack stated,

> This allows me to make better use of my time in the classroom. If I know that an exam—on average—can be completed by students in 20 minutes, then I allow this amount of time during class for the exam and then prepare new learning materials for the remainder of the class. Why waste 25 minutes of a 45-minute class?

Jack also presented challenges to the use of learning analytics. He posited that even when analytics have suggested that an exam should take 20 minutes to complete, other things may come into play disrupting the natural flow of the classroom activities. Poor internet bandwidth, batteries going dead on students’ mobile devices, or the lack of technology in the classroom have often thrown a wrench into his best intentions. Jack stated, “Even with the best laid plans, learning analytics are only a guide.”

Another interviewee, Jackie, presented a differing perspective on the use of learning analytics. She noted that she was not a computer immigrant, rather a late adopter to technology. As a full-time professor, she used learning analytics as an integral part of her teaching responsibilities. She also noted that learning analytics have afforded full-time teachers the capacity to make better use of their instructional time—especially when presented with over a hundred students each semester and multiple course offerings. She noted that the *attendance analytics* helped to alleviate time spent keeping up with attendance in her courses. One of the affordances of this analytic is that it not only calculates the number of absences, it automatically generates an email to the student about their missed class. When her teaching responsibilities were reduced to two campus courses per semester, she chose not to use learning analytics or the learning management system any longer. Accordingly, Jackie conveyed,

> I saw students completing a 16-week course in 45 minutes. How? The students were savvy to features built into Canvas. One student would take the exam and then print out the answers and give the exam answers to others in the class. I could look at the logins and time spent in the course and know that the student had obtained the answers and was merely filling in the blanks and checking the boxes. I didn't need this headache. I chose to stop using Canvas and teach and test in the classroom. If students don't achieve, it's my fault.

As a full-time instructor, Jackie believed that the benefits of using analytics to guide the efficiency and effectiveness of teaching and learning were significant. But as an instructor with a diminished workload, she didn't recognize the same results. Although learning analytics, as discussed in the survey findings, were not typically used to detect students' cheating, this interviewee noted it as an affordance.

Challenges of using learning analytics in practice. As indicated previously through the survey data, the review of literature, and with the experts, challenges of using learning analytics in practice were evident and pronounced. All four interviewees mentioned the challenges of using learning analytics when asked the question: *What if any are the mitigating factors influencing your use of learning analytics?* While they chose to focus most of the time allotted in the interview to the affordances of learning analytics, insight into the problems of implementation and ongoing use were detailed. The sub-themes evident from the preponderance of data suggested that time constraints and lack of training, professional development opportunities and incentives at their respective places of employment were viewed as stumbling blocks.

Time constraints. Although the experts noted their use of learning analytics helped them to make better use of their time in the classroom, all four of the experts conveyed issues with time as it related to their acquisition of skills, learning the analytics, and successfully implementing them. Jackie stated, "Often, I don't have the time to use learning analytics as it is often too difficult to learn and at times it diverts from my teaching." Also in agreement, Marianne maintained, "There are so many features that I have never learned." Marianne and Jackie concurred that one of their main issues included a high workload and deliberate choices not to use their time off work to complete training classes. When asked about Jackie's workload specifically, she commented that using learning analytics often increased her daily work time. Along the same line, Jack avowed:

> If I pull an Excel worksheet, I then have to analyze it and make the data actionable. Without action, it is only a list of statistics. That means that I not only spend time accessing and analyzing the data, I then have to make

> improvements, changes, contact students, make decisions, change my upcoming lectures—and on and on. One simple analytic could lead to hours of extra work.

All of the interviewees remarked about their heavy workloads, teaching as many as six different courses each semester. In this manner, Marianne added, “I teach six classes plus have other responsibilities; there is no time to learn analytics.”

Lack of training, professional development and incentives. All four experts were impassioned about their dissatisfaction with training and professional development initiatives**.** Furthermore, a lack of incentives to use learning analytics were also pronounced. Jackie, that had previously held a full-time working schedule, but had since switched to a reduced teaching load, offered insight into this dilemma. Specifically, she criticized current professional development opportunities as not being sufficient to meet the needs of the instructors. Even when a course is offered (and one was presented on learning analytics at her place of employment), she added that follow-up to determine whether the instructors gained the knowledge to adequately implement the analytics in practice was not conducted. Jackie stated, “I only learn what I can apply; I need repeat courses to learn and then to apply.” When asked about professional development and training, Jackie purported,

> Who’s going to teach it to me? Why should I? I haven’t attended any other professional development sessions other than one on learning analytics. If I could get more training, I would do it. But, no one has encouraged me to do this. Not one of my supervisors encourage the use of analytics; they don’t support my efforts. When I was non-tenure track, there was no obligation to take professional development. I took them anyway and never received praise. When I worked full-time, no one cared if I completed professional development except for title

> nine and sexual assault seminars. I had basically no training and no application follow-up. There should have been a program in place to ensure success to make sure it is learned and applied accurately.

Further delineating on the use of analytics, this Jackie replied, “Absolutely, I would use analytics more often if my pay scale was adjusted; if I received a pay raise I would use it more often.” Speaking from a supervisory role, this instructor concluded:

> Because there are so many adjuncts, the amount of implementation (of learning analytics) goes down. There simply is no financial incentive to be a strong user or expert. The level of skill has decreased. The problem is with the work load. Professional development classes on campus—I can’t attend. Online professional development classes aren’t productive as I don’t want to use my time off doing a class. This technology can serve students and instructors well, but in the end, it serves the college better with less dropout and failures. But many of the instructors balk at the use of an LMS or any of its features. I don’t know one person that uses learning analytics at my place of employment. There is a big Mississippi River of what learning analytics can do and what our adjuncts and students can benefit from. But there is no bridge there. Unless there is integration and administrative support, it won’t happen.

Culture of the Institution. Experts noted that the culture of their respective institutions often shaped their experiences and practices with technology. Marianne, reflecting on the culture of her institution, added, “If I had a progressive team of professors, I would use it more.” She noted that professional development must accommodate schedules and provide adjuncts with a sense of feeling of care or concern—and that the technology produced desirable results. If

not, Marianne proclaimed, “They won’t do it.” In reference to the institution and incentives, Jackie affirmed,

> You can’t do it like police force mentality. There should be a reward. They are paying all this money for the product and not using it. It is like paying for an espresso machine and never using it. But it looks good.

Also, offering insight into the culture of the institution, Marianne insisted, “Most of my colleagues think they [learning analytics] are bull crap and too much work; they have no skills and are stuck in old school education.” Other interviewees were vocal about the lack of professional development opportunities and incentives. Accordingly, Jack asserted, “There has never been a professional development course at my institution to guide me in analytics integration.” Reflecting on the institutional culture and resistance to change, Marianne acknowledged,

> I did take one learning analytics course through the book company, but not through the college or university. It just isn’t their comfort zone. The culture at the college is toxic–they don’t want change. The teachers’ excuse is academic freedom. Teachers don’t want to change. There is a lack of time to teach six classes plus other responsibilities. There just is no time to learn analytics.

Marianne, also reflected on the culture of her institution in a different way. Referring to her university’s lack of technology and learning analytics as a prioritization, Marianne declared:

> My institution has their own proprietary platform and IT SUCKS! It is old school and one dimensional.

Marianne further added that the buzz-word and priority focus at her institution has been *assessment.*

Monitoring and Comparing Students' Progress. All interviewees remarked about their use of learning analytics either to monitor students or to assess or compare students' progress within the course. Monitoring often involved checking logins to the course, determining the number of discussion posts, comparing students' work and grades, assessing patterns of use and non-use, and time spent in the course shell. Reflecting upon the interviews with the experts, sub-themes appeared involving the targeting of at-risk students, monitoring of learning outcomes and retention.

Targeting At-risk Students. All of the experts commented on their use of analytics to target those students at risk of failing the course. Marianne described her efforts at targeting low achieving students:

> In the gradebook, I sort by grade and look for those with a C or lower. I then email them. I send out an early alert warning [through administration] for those that have a C, D or F. I contact them three times [students]. I can rescue most of them. But to keep kids in class–it takes teachers to go the extra mile.

Marianne further added, "If I need the data [learning analytics], I can find it." Yet she also noted that an informed teacher should know where their students are at—without the use of analytics. Reflecting on the need for instructor intervention to help students, Marianne surmised, "Numbers only tell half of the story." In this manner, the targeting of at-risk students may begin with analytics, but that is only the initial step. She then initiates contact with the student by addressing them before or after class or through the use of email messages. She said that although a paper trail is great, it often does not evoke student change.

Learning Outcomes. All interviewees agreed that learning analytics have been used to assess learning outcomes. They specifically noted that learning analytics were utilized to

determine student progression within the course and to manage engagement. They cited that learning analytics helped them to specifically measure learning outcomes to determine the completion of goals. Jason professed,

> For each course, I have associated learning outcomes. They are posted and visible for all students to see within the learning management system. Each learning activity is linked to an associated learning outcomes. I use analytics to monitor the assignments and assessments that are linked to each learning outcomes. Occasionally, the analytics are used as a means to evaluate the learning activity. Often, I have revised these activities to help increase or ensure learning outcomes. The analytics make measurement easy.

In reference to frozen data, which is often displayed in the form of charts and graphs, Marianne surprisingly affirmed,

> I don't look at the frozen data, learning analytics snapshots or dashboards, unless a student's grade isn't cutting it. I then check to see logins. I can also get many analytics on the student's level of engagement in Learn Smart. I use analytics to measure learning outcomes and goals within the course. If learning outcomes aren't being achieved, I make changes. Sometimes the change is with my teaching style.

Retention. All four experts used learning analytics to support retention efforts in their respective courses, although some mentioned that the benefits were more pronounced for the administration rather than the student. Learning analytics were used by some of the experts to provide an early-warning system. Jackie mentioned the *what if* feature that is available through her learning management system's analytics for students. In this connection, students have the capacity to visit their gradebook and insert targeted grades. The system calculates the targeted grade along with previously earned scores reflecting a speculated ending course average. Jackie noted, "What if they scored 80 on the upcoming exam—what would be their ending course average look like?" This tool, although it can guide students in the acquisition of their desired grade and possibly promote retention—it has also served an undesirable purpose for some of the students choosing to use it. In this connection, Jackie assessed,

> Students can use the *what if* feature in Canvas to determine the least amount of points needed to pass a class. Although this can promote retention, it also promotes the least amount of work needed by the student. Students are point driven and not necessarily driven by learning.

Conclusion

This chapter presented a two-phased research approach—a dominant-less dominant design as proposed by Creswell (1994). The analyses of the data centered upon three research questions and a descriptive analysis of the respondents. Respondents' professional data revealed a concentration of respondents from the U.S., with southern states closest to the conference offering the greatest representation. Females were slightly more represented in this study than males. There was a unique distribution of respondents with the majority reporting their length of service was either less than five years of service or eleven to twenty years of service. Fully

online institutions were least represented in the survey while the majority of respondents were employed by universities with or without masters and doctorate degree programs. Most of the respondents had earned at least a master's degree and reported their academic rank as professor.

Consistent with the literature review, the majority of the respondents reported using Blackboard as their learning management system, followed by Canvas and Moodle. Respondents tended to use their learning management system at least weekly.

Focusing upon the instructors' usage of learning analytics to reflect upon their teaching practices, curriculum and or pedagogy, interesting results were rendered. The majority of the respondents reported never using learning analytics and 11% reported previous but not current use. Therefore, two-thirds of the respondents have either never used learning analytics or previously used them and consequently discontinued use. When learning analytics were used, the lowest reported usages were categorized as being utilized *most of the time.* It was apparent that when instructors used learning analytics, they were used pro-actively in a supervisory means as a watchful guardian rather than using them as a watchdog to spot unethical conduct. Usage often entailed the monitoring of discussions, checking logins, using the analytics as an early-alert system and or to reflect upon their own teaching practice.

This study explored the use of learning analytics to reflect upon student learning and outcomes. Respondents were surveyed to determine if they used learning analytics to (a) enhance student learning, (b) provide a personalized student learning experience, (c) manage student engagement in the course, (d) determine student progression; (e) measure learning outcomes and goals, and (f) improve retention. Less than 15% of the respondents reporting using learning analytics specifically to inform learning outcomes and goals. More instructors failed to use learning analytics rather than to use them *most of the time* in this endeavor. Most of

the usage was assessed on an occasional (seldom) basis. With a total sample size of 114, with only two respondents stating they use them *most of the time* to address learning outcomes and goals, reported usage was quite low.

Key challenges to the buy-in and adoption of learning analytic were evident. Two-thirds of the respondents noted either never using learning analytics or using them and since discontinuing use. The most frequent cited reasons behind the discontinuation of learning analytics included a lack of worth and diverting from teaching responsibilities. Other reasons cited more often included (a) lack of professional development or incentives, (b) insufficient training on how to use the analytics, (c) deficient evidence that learning analytics altered their method of teaching, and (d) their institution's culture. When asked specifically in an open-ended question about the challenges of using learning analytics, three themes emerged including the lack of time to learn and use analytics, problems with learning management systems and the analytics packages, and insufficient professional development, training and or incentives.

Analyses of expert interviews yielded three themes including, (a) efficient and effective use of time spent teaching in the classroom, (b) challenges of using learning analytics in practice, and (c) monitoring and comparing students' progress. The timing of exams, recycling of information, planning lectures, monitoring logins, calculating postings, and comparing students' work were viewed as affordances of learning analytics. On the other hand, the challenges were pronounced, including a lack of time, heavy workload, insufficient professional development training and incentives, a culture of resistance and issues with change.

Chapter 5

Discussion

Chapter 4 presented a two-phased research approach for the study of instructors' use of learning analytics in higher education. A dominant-less dominant design as proposed by Creswell (1994) was utilized—incorporating both surveys and purposefully selected interviews. Population, setting, instrumentation, data-collection procedures, and data analyses were presented. The value of this study was derived from its fit with previous research in that it filled a gap in the literature exploring the nature and extent of faculty usage of learning analytics. The results from the study were organized into major sections. The first section included the examination of the respondents through the analyses of descriptive variables. The second section involved the respondents' use of learning management systems. The final section involved thoughtful reflections on the three research questions with emphasis first on the survey findings and then secondly from an exploration of data from the expert interviews. The purpose of the study was addressed in the following research questions:

RQ1: How do instructors at institutions of higher learning explore learning analytics to reflect upon their teaching practices, curriculum, or pedagogy?

RQ2: How do instructors at institutions of higher learning explore learning analytics to reflect upon student learning and outcomes?

RQ3: What are the perceived key challenges to the adoption or use of learning analytics by instructors at institutions of higher learning?

Summary of Findings

Learning analytics have been heralded as one of the technologies changing and capable of reshaping the landscape of higher education (Bichsel, 2012; Dahlstrom & Brooks, 2014; Dahlstrom et al., 2014; Educause, 2012; Gasevic, Dawson, & Siemens, 2016; Johnson et al.,

2014; Johnson et al., 2016). Yet, it was not apparent in the literature that studies had reflected specifically upon the nature and extent of instructors' buy-in, professional development opportunities, knowledge and use of learning analytics in teaching practices. The present research study addressed the gap in literature between the promises presented through research studies on the affordances of learning analytics and actual practice by instructors. Siemens (2012) referred to this as the research and practice gap, which is well-known in numerous fields and has been evident with learning analytics. Beer and Tickner (2014) called this a "… gap between the rhetoric around the virtues of e-learning and the complicated reality of the e-learning lived experience," (p. 242). Siemens (2012) suggested that the work of researchers are often not translated into practice. Mirzajanin and colleagues (2014) reported that "Nevertheless several universities faculty members have determined to integrate ICT (information communicaton and technology) into their training, some faculty make the purposeful selection not to do so" (p. 25). With the low usage of learning analytics as reported through the survey, it would appear that the research and practice gap is evident with learning analytics. The gap between the rhetoric and the virtues appeared to be widespread in the research findings with instructors often recognizing the benefits yet failing to incorporate them into their teaching practice. In agreement with Siemens (2012) and Mirzajanin and colleagues (2014), the findings from this study suggest that the work of the researchers has not been translated into teaching practice.

Chatti and colleagues (2015) ascertained, "Currently many of the systems are data rich, but information poor" (p. 12). This was addressed by some of the respondents and interviewees with one referring to it as a "mathematical monster providing insufficient information in a timely and useful manner." According to Johnson et al. (2014), "While interest is considerable, higher education in general has yet to fully embrace these sorts of processes…but the potential of using

data to improve services, student retention, and student success is clearly evident" (p. 12). According to Dahlstrom and colleagues (2014), even though instructors have valued the tools within learning management systems as having great potential to aid in student learning, many of them are often underused, referring to this as an *underutilization phenomenon* (p. 11). The underutilization phenomenon was evidenced through the low use of learning analytics by instructors in the present study. This discrepancy may be attributed to the intricate nature of the analytics, lack of time coupled with a heavy workload, and a problematic integration process (including a lack of professional development, training, follow-up, learning opportunities and incentives).

Therefore, the present study addressed the gap in literature by exploring the extent, nature, and use of learning analytics by instructors in higher education to reflect upon teaching and learning. The data from the survey and interviews provided needed information about the lived experiences of instructors in higher education. A summary of findings addressing the research questions combining data derived from both the survey and the interviews were addressed with a thoughtful reflection on change theory and TPACK.

Survey respondents and interviewees. Responses from 39 states in the U.S. were analyzed along with and six additional countries. Of the respondents, there was a higher representation of females completing the survey than males. New instructors and those that had the highest years of service were the least represented in this study. Instructors with one to twenty years of service were more apt to complete the survey. Fully online institutions were minimally represented; universities with masters or doctorate programs had higher representation. The majority of the respondents reported their academic rank as professor (54%) followed by instructors (42%).

Consistent with the literature review on the widespread use of learning management systems, the majority of the respondents reported using Blackboard, followed by Canvas and Moodle. The proprietary learning management systems by Pearson was used by slightly more than six percent of the respondents and utilized by two of the expert interviewees. When asked about their usage of learning management systems, the majority of respondents reported using them at least weekly. Ten percent of the respondents noted never using a learning management system. Only one-third of the instructors were currently using learning analytics.

The four interviewees were purposefully selected due to their present or past usage of learning analytics. Special consideration was given to those that had more extensive background knowledge and use of learning analytics in their present practice. One interviewee was purposefully chosen because she had once used learning analytics but had since discontinued use. Both affordances and challenges were conveyed through the interviews.

Change theory and TPACK. Ertmer and Ottenbreit-Leftwich (2010) have affirmed that technology integration relies on changes in teaching practices, belief systems, pedagogy, content knowledge, instructional practices, and resources. Fullan (2011) referred to the *stratosphere* as the intersection of technology, pedagogy, and change theory. Researchers contend that change is often hampered due to a lack of knowledge, belief systems, low self-efficacy, lack of teacher-centered focus, and institutional pressures to conform (Bain & McNaught, 2006; Ertmer & Ottenbreit-Leftwich, 2010). In the present study, instructors often cited heavy workloads, insufficient knowledge, and lack of understanding as obstacles to implementation and continued usage.

MacFadyen and Dawson (2012) recognized the resistance of institutions to change or evolve over time. Mishra and Koehler (2006) have acknowledged the fear of change that is often

exhibited when implementing new technologies. Lack of time to learn, implementation impediments, insufficient support and lack of buy-in were documented in this study. Resistance to change was evidenced within this study and illuminated by the following responses, “Most of my colleagues think it is bull crap and too much work” and “The culture at colleges are often toxic–they don’t want change.” Ertmer and Ottenbreit-Leftwich (2010) suggested that numbers alone are not enough to affect change, proposing, “… greater attention is needed to the accessibility and presentation of analytics processes and findings so that learning analytics discoveries also have the capacity to surprise and compel, and thus motivate behavioural change” (p. 161). The findings have suggested that instructors have not been convinced that change is needed by incorporating learning analytics. Respondents in this study noted a lack of initiatives or incentives to promote the use of learning analytics. To illustrate this point, and simply stated, Jackie inquired, “Why should I (in reference to using learning analytics). Marianne admitted, “Some teachers without a math or business background just don’t want to be bothered.”

Kotter (1995, 2016) delineated eight steps in the successful implementation of change. He noted that the first step in efficiently controlling change is one that instills a substantial sense of urgency—thereby appropriately necessitating high levels of motivation. Without motivation, the movement often dissipates. Although urgency has been clearly demonstrated due to the plethora of literature and research on learning analytics, the extent of buy-in by instructors and their particular use patterns were not evidenced in this study. In light of Kotter’s change model, the present study reflected that instructors’ buy-in was not aggressive, widespread nor substantial. Furthermore, Kotter’s model relied upon a team of professionals issuing guidance and support. The findings from this study suggested a lack of supervisory and administrative support for the use of learning analytics. Therefore, the findings of this study failed to

substantiate the first two steps in Kotter's change model, involving urgency and administrative support.

Mishra et al. (2009) maintained, "Throughout history new technologies have been hailed as the next, best thing" and often faculty and institutions chase the latest and greatest innovations (p. 48). With the case of learning analytics, it has been heralded as one of the major future game-changers in higher education by researchers (Bichsel, 2012; Dahlstrom & Brooks, 2014; Dahlstrom et al., 2014; Educause, 2012; Gasevic, Dawson, & Siemens, 2016; Johnson et al., 2014; Johnson et al., 2016). Findings from this study have suggested that it may be a game-changer for some, but not necessarily for instructors in higher education.

Mishra and Koehler (2006) and Koehler and colleagues (2013) urged the pursuance of a deep understanding of technology through training. They posited that teaching with technology is difficult to do well. The most frequently cited challenge of learning analytics as reported in this study was the lack of incentives, training and professional development opportunities afforded to instructors. Merely knowing how to use technology does not mean that the technology is useful to teaching and learning (Ertmer & Ottenbreit-Leftwich, 2010; Fullan, 2011; Karaman, 2012; Koehler et al., 2013; Mishra & Koehler, 2006). As some researchers and theorists have suggested, technology has not been implemented to serve only as an add-on—but rather as part of a whole (Mishra, Koehler, & Kereluik, 2009; Strudler & Wetzel, 1999). The findings suggested a staggering low usage of learning analytics; this may add credence to the view that it is an add-on and not an integral part of teaching practice.

Teaching Practice, Curriculum and Pedagogy. Papamitsiou and Economides (2014) directed a rigorous review of literature on the empirical evidence supporting the use of learning analytics in higher education. Their study suggested four key capacities including pedagogy

(estimation of course outcomes, assessment, and reflection), teaching and learning, networked learning and resource management. Dietz-Uhler and Hurn (2013) urged the use of learning analytics in learning management systems to shape students' progression through a course by and with a more personalized learning experience. Despite these affordances, findings from the *Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations* suggested that analytics have experienced the least acceptance among instructors (2012b). In the present study, when learning analytics were used by instructors, their use was low reflecting seldom or *some of the time* usage rather than *often* or *most of the time* use. The lowest reported learning analytics usages were categorized as being utilized *most of the time*. Less than 20 percent of current users reported at least *occasional use,* therefore confirming the findings from the aforementioned report that learning analytics have truncated acceptance with instructors. When learning analytics were used, their use often involved what might be deemed positive, supervisory and non-punitive. Often, their usage was supervisory in nature as a watchful guardian rather than as a watchdog for unethical conduct. In this manner, instructors tended not to use analytics to drop students for non-participation nor to detect cheating. Learning analytics were used more often to monitor discussions and or the number or postings, to check logins by students, to serve as an early-alert system to determine students at risk, and to reflect upon their own teaching practice. In addition, instructors also used learning analytics to monitor system generated data from clicks, swipes or sensors, to manage student engagement in the course, and to assess mean/standard deviation of students' test scores. In reference to curriculum, some respondents noted that learning analytics were used to refine their course, to provide a personalized student learning experience, and to refine exam questions. Even though the affordances were noted, the actual use of learning analytics to inform teaching practice,

curriculum and pedagogy remained quite low. All of the experts agreed that learning analytics were used to inform teaching and learning, curriculum needs and changes, as well as pedagogy. What appeared to be standard use of learning analytics by experts, doesn't necessarily transfer to instructors as a whole.

Student learning and outcomes. Papamitsiou and Economides (2014) suggested that student learning and outcomes are central to discussions on learning analytics. In the present study, respondents were surveyed to determine if they used learning analytics to (a) enhance student learning, (b) provide a personalized student learning experience, (c) manage student engagement in the course, (d) determine student progression, (e) measure learning outcomes and goals, and (f) improve retention. Less than 15% of the respondents reported using analytics to impact learning outcomes and goals.

When asked directly about the measurement of learning outcomes and goals, more instructors reported not using learning analytics (n = 10) rather than using them *most of the time* (n = 2). With the total sample size of 114, and with only two respondents, the utilization of learning analytics to measure learning outcomes and goals were reportedly very low. When learning analytics were used *most of the time* by instructors, their use tended to center around enhancing student learning, managing student engagement in the course and determining student progression within the course.

Several researchers have presented the affordances of an early-warning system for determining students are at risk (Baker & Siemens, 2011; Lykourentzou et al, 2009; MacFadyen, 2011; Purdue University, 2013; Romero-Zaldivar, 2012; Wolff & Zdrahal, 2012). Clow (2012) acknowledged the use of learning analytics to inform interventions. Expanding upon Clow's cyclic theory of learning analytics, Oblinger (2007) reflected upon five steps in the learning

analytics process emphasizing prediction, action, and change. According to Romero-Zaldivar and colleagues (2012):

> An important factor that contributes toward the effectiveness of a learning experience is the ability of instructors to monitor the overall learning process and potentially act based on the observed events. In the ideal situation, an instructor monitoring all the events taking place in a learning environment would have a privileged position to adjust whatever parameters are available to improve the overall experience for the students. But this hypothetical scenario is still very far from reality in today's educational institutions and, even worse, there are several forces pulling away from this objective. (p. 1)

In this connection, the present study reflected upon the affordance of using learning analytics to monitor students work within a learning management system, however, concurring with Romero-Zaldivar and colleagues (2012), there appeared to be forces that were preventing initial use and or successful implementation. Reflecting on Clow (2012), Oblinger (2007) and Romero-Zaldivar and colleagues (2012), when learning analytics were used by instructors, in the present study, their usage was low reflecting *seldom* or *some of the time* usage rather being used *often* or *most of the time*. Findings the survey in this study suggested that learning analytics—when they were used—assisted in the early detection of students at risk. A follow-up question targeting the use of learning analytics to provide intervention, indicated that they were typically *seldom* or *sometimes* used. So, although learning analytics were informative as far as helping to pinpoint students at risk, it was apparent that forces or situations prevented action. On the other hand, the experts agreed that learning analytics were useful in the monitoring and comparing of students' progress, targeting at-risk students and providing intervention through the use of student contact

(in person, messages or phone) and campus referral systems. When narrowing in on actual instructors' practice, it was not apparent that learning analytics were used often to target at-risk students nor to provide intervention—although these affordances were cited quite often in the literature review.

Key Challenges. *The Learning Analytics in Higher Education Report* from Educause offered the most up-to-date information on the state of learning analytics (Arroway et al., 2016). Arroway and colleagues (2016) suggested that learning analytics have been an interest rather than a priority. The present study confirmed the aforementioned report that while faculty issue their support of learning analytics to improve student outcomes, their actions often denote the opposite. This action-lag was evidenced in the data with experts also noting a lack of support and culture of resistance at their respective institutions. Over half of the respondents affirmed that they had never used learning analytics while 11% noted that they had previously used them but discontinued use. Therefore, two-thirds of the respondents either never used learning analytics or previously used analytics, and then ceased. There is apparently an issue with buy-in, implementation and continuation of use. One interviewee proclaimed,

> But many of the instructors balk at the use of an LMS or any of its features. I don't know one person that uses learning analytics at my place of employment.

While conducting a snowball sampling procedure to find experts, one information technologist at a major institution of higher learning reported that they could not recall any instructors that use analytics. This individual then posted on a university online instructors' forum inquiring about instructors' usage of analytics. Not a single response was garnered.

A question was posed only for those respondents that stated that they had previously used learning analytics and consequently discontinued use. This question inquired into their

reasoning behind their change in use. The most frequently cited reasons behind the discontinuation of learning analytics in their practice was a lack of worth and the diversion of time from their teaching responsibilities. Other reasons included a lack of professional development or incentives to learn analytics, insufficient training, inadequate evidence that learning analytics altered their method of teaching, and the culture of the institution. When respondents elaborated in an open-ended question about key challenges on the survey, they often cited lack of time to learn and use analytics, problems with their learning management systems and the analytics packages, and inadequate professional development opportunities, training or incentives. One interviewee proclaimed, “There are no financial incentives to be a strong user or expert.”

According to Strudler and Wetzel (1999), instructors must recognize the fit between the method of teaching with technology and learning (pedagogical fit). They suggested one-on-one support with instructional specialists, consulting, modeling of technological applications, and an open door policy for assistance. Pedagogical fit was not evidenced in the present study. Inadequate assistance and insufficient support were noted. As one expert—Jane mentioned, “Who’s going to teach it to me?” In agreement with Strudler and Wetzel, there must be a good balance between pressure to use the technology and instructional support. In like manner, Marianne (an expert) exclaimed, “You can’t do it like police force mentality; there should be a reward.”

Implications, Considerations and Recommendations

The present research study provided an examination of the extent and use of learning analytics in higher education. Findings of the current study are consistent with the mounting evidence that major challenges are impeding implementation of learning analytics by instructors

in higher education. While the use of learning analytics by instructors appeared to be quite low, the potential virtues of this technology were evidenced. A lack of buy-in by instructors, a culture of resistance, lack of teacher change, and inadequate professional development opportunities and incentives tended to overshadow the fireworks of the learning analytics movement.

Dating back to the early 1990's, researchers and scholars reported on the use of technology including preservice teacher preparation, expectations and realities (Strudler et al.,1999; Strudler & Wetzel, 1999). Accordingly, Strudler and Wetzel (1999) recognized that an informed strong committed leadership of the administration must be present for successful technology implementation. The backing of the technology by the leaders has often been considered an integral part of the change process. Strudler and Wetzel (1999) and Strudler and colleagues (1999) suggested that impediments to integration have also been due to a lack of professional development and technical support. Training must integrate technology into the curriculum and not merely serve as an add-on. Professional development opportunities should include workshops, group classes, quality and comprehensive training, and offerings that accommodate a variety of styles and work schedules. Findings from the present study suggested that the challenges with a strong committed leadership, lack of professional development, training and support that were present in the late 1990's, are still evident in higher education today.

Strudler and Wetzel (1999) also suggested the use of grants and institutional wide initiatives to enhance or hone in on instructors' technological skills—including stipends, workshops, and sabatical leaves. Incentives and initiatives to learn and implement analytics by instructors were not evidenced in this study. Another issue that was cited in the 1990's (Strudler & Wetzel, 1999) was the lack of time instructors had to devote to technological advances. This

issue was noted as one of the major obstacles with learning and using analytics in the present study.

Mirzajanin and colleagues (2014) exposed significant factors that affected implementation, including the availability of resources, skills, time and leadership and a lack of a reward system for instructors (whether it be persuasion, incentives, recognition, or respect). These factors were evidenced in the present study. It is apparent that while technology has continued to expand and become more complex, higher education has continued to struggle with the same fundamental issues as they did in the 1990's—and with learning analytics not being the exception.

Limitations and Future Research

The present study was exploratory in nature, examining the nature and extent of learning analytics usage amongst instructors in higher education. Therefore, only descriptive analyses of variables were used to explore the topic at hand. A limitation with this design of this study involved the of self-report data. Instructors were offering their beliefs as to their estimation of use—which may or may not reflect actual usage. Usage may be minimized or exaggerated due to either their enthusiasm with or disenchantment of learning analytics. In this connection, there may be a propensity for instructors to use analytics less than what they report, and in contrast, it may portray the opposite. It would be advantageous for a study to compare self-reported usage with actual usage (data-driven) to determine whether self-report studies in reference to analytics are reliable.

Another limitation of this study is also in reference to privacy issues and self-reporting. Instructors may have been hesitant to offer information that could link them to the study and jeopardize their position at their institution of higher learning. This may be the case more so for

the interviewees rather than the respondents. This may have resulted in more positive reflections on their use of analytics and less emphasis on the challenges.

Notetaking instead of using a recording device was a limitation in this study. The slower process of writing out quotes and major points resulted in some pauses, distractions and/or interruptions. The physical locality of the interviews, at the conference and at other public facilities were not optimal.

Bichsel (2012a, 2012b), in the *ECAR Study of Analytics in Higher Education,* reflected on the eminence of learning analytics at institutions of higher learning. Findings from this study concluded that instructors that used more advanced tools exhibited higher satisfaction ratings than others. Relating this to the present study, it is possible that the interviewees' enthusiasm might have overshadowed a prejudiced and more inflated and optimistic view of learning analytics in practice. Likewise, disenchantment, as documented by one of the interviewees and some of the survey respondents may likewise reflect poorly upon the usage of learning analytics, while the majority of users may not feel the same way.

It would be advantageous to conduct a more in-depth analysis of instructors' usage of learning analytics providing statistical analysis of variables that might offer greater insight. Perhaps, studies to determine whether impediments to instructors use of learning analytics may be overcome through research, professional development, budgeting of time and resources, rewards and support should be conducted. Future research would be useful that focuses on successful and unsuccessful implementation processes at institutions of higher learning. Since instructors' change appeared to be an issue with the implementation of learning analytics, a study specifically addressing the change process and adoption might be warranted. Studies targeting the use of learning analytics in particular fields of study might also be useful to practitioners.

Although privacy and confidentiality issues were beyond the scope of the present research, it remains an issue in higher education with the inclusion of third party vendors, analytics and predictive models generating actionable intelligence. With the implementation of technologies with advanced features, such as learning analytics, the likelihood of unintended disclosure may increase. Instructors or administrators may agree that there is an ethical obligation to act on knowledge about students gained through analytics, yet the sharing of these insights must be framed in a way that provides benefits and not harm.

While most of the affordances reported by the instructors using learning analytics were student-centered, one respondent noted that learning analytics were used to target the performance of other instructors. In *The Learning Analytics in Higher Education Report* (Arroway et al., 2016), the researchers noted, "Faculty, already wary of and often resistant to measurement, may be suspicious of motives, data quality, and interpretation" (p. 13). If instructors have been concerned with unfair evaluations and/or misjudgments, their use of a learning management system might be affected. One respondent added that learning analytics were used in a supervisory manner to compare the work of instructors. In this connection, analytics were used in a watchdog type fashion to compare statistics on students' attendance, mean scores on tests, and achievement of outcomes amongst and between instructors. This brings into question issues of academic freedom. Should instructors' online courses be scrutinized or evaluated by others in supervisory positions? Are instructors informed that others may be observing their online presence? Does the presence of a third party alter the experiences of the students and or the instructor? Studies addressing these questions would be warranted.

One of the ethical considerations that must be addressed is the issue of disclosure. The questions targeted instructors' use of analytics within their teaching practice, disclosing potentially sensitive information about their own teaching practices but also delicate information about their institution of higher learning. Therefore, the institutions that were discussed during the interviews were not disclosed. The interviewees names were not released to help prevent possible repercussions as some of the information cited could be considered pointed and direct. Pseudonyms were used to protect identities.

Significance and Conclusion of the Study

The significance of this study is that it provided an exploration of the extent and nature of learning analytics use in higher education by instructors. No other similar study was found in the literature review focusing on the use of analytics from instructors' lived perspectives. From the study and the review of literature, it is apparent that learning analytics have the potential to revolutionize higher education. Yet, in spite of technological advances in higher education, the buy-in of administrators, instructors and the university as a whole, reportedly are astonishingly low. As evidenced in this study and apparent in the literature, a gap exists between research and teaching practice incorporating learning analytics. The analogy offered in this study compared learning analytics to the Mississippi River–offering a river of information—but failing to offer a bridge to cross over. Another analogy likened learning analytics to an expensive espresso machine that has never been used—but looks good.

The literature review demonstrated that successful implementation of new technology in higher education has been dependent upon important factors namely: knowledge and skill, professional development, availability of time, strong leadership and a system of rewards. All of these were noted as major challenges with the implementation and use of learning analytics in

this study. Without the existence of knowledge and skills, users are unable to use the technology at hand. For buy-in, implementation and successful change, the availability of resources must be present and made available to instructors, such as personnel and assistance, professional development and incentives. Availability of time, although intuitive is absolutely critical to buy-in and successful implementation. Without devoting the time needed and required, successful and substantive implementation of learning analytics is likely to be uneventful.

Appendix A

Faculty Use of Learning Analytics Survey

Q1 The purpose of this research project is to determine faculty usage of learning analytics tools. This is a research project conducted by Kendall Hartley, Associate Professor of Educational Technology and Janet King, PhD student at UNLV. You are invited to participate in this research project because you teach courses or have taught courses in an institution of higher education in the past 5 years. Your participation in this research study is voluntary. If you decide to participate in this research survey, you may withdraw at any time. The online or paper survey will take approximately 10-15 minutes. Your responses will be confidential and we do not collect identifying information such as your name, email address or IP address. If you have any questions about this research study, please contact Janet King at (702) 406-5558. Research has been reviewed according to UNLV IRB procedures for research involving human subjects. Do you grant your permission to participate in this research project?

❍ Yes

❍ No

Q2 In what state and country do you work?

Q3 What is your gender?

❍ male

❍ female

- other
- prefer not to say

Q4 How long have you worked in higher education?

- first time instructor or professor
- 1-5 years
- 6-10 years
- 11-20 years
- 21 or more years

Q5 Where do you work?

- community college
- 4-year college
- university not including masters and doctorate programs
- university including masters and doctorate programs
- fully online institution (whether college or university)

Q6 What is your level of education?

- less than a four-year degree
- bachelors
- masters
- doctorate

Q7 Which of the following best describes your academic rank during the current academic year?

- professor
- instructor
- no academic rank

Q8 Which learning management system do you use at your place of employment?

- Blackboard
- Canvas
- Desire 2 Learn - D2L
- Moodle
- Sakai
- Pearson eCollege
- Jenzabar e-Racer

❍ I don't know which learning management system is used at my place of employment.

❍ Other, please specify ____________________

Q9 How often do you use this learning management system at your place of employment (on campus or elsewhere online) for the courses that you teach?

❍ daily

❍ weekly

❍ monthly

❍ a few times each semester

❍ never

Q10 According to Educause, learning analytics refers to the "use of data, statistical analysis, and explanatory and predictive models to gain insights and act on complex issues" (Bichsel, 2012: p.6). Some learning management systems have learning analytics incorporated, and they may be referred to as course analytics or academic analytics. Instructors may refer to these to determine the number of page views, the progress of students, to view bars and charts denoting progress or usage, to determine the average score on an exam, the number of posts on a discussion board and the number of log- ins (for examples). Do you use learning analytics within your learning management system for any of the courses you teach?

❍ yes, I currently use learning analytics

❍ no, I have never used learning analytics

❍ I previously used learning analytics but I don't use them anymore

Q11 How do you currently use learning analytics in the courses that you teach?

	Never	Don't know what it is	Seldom	Sometimes	Often	Most of the time
Frozen Data (snapshots or dashboard(d)	❍	❍	❍	❍	❍	❍
System generated data (from clicks, swipes or sensors)	❍	❍	❍	❍	❍	❍
Enhance student learning	❍	❍	❍	❍	❍	❍
To refine my course	❍	❍	❍	❍	❍	❍

To provide a personalized student learning experience	❍	❍	❍	❍	❍	❍
To refine exam questions	❍	❍	❍	❍	❍	❍
To determine time needed for assessments or assignments	❍	❍	❍	❍	❍	❍
To monitor discussions and or the number of posts	❍	❍	❍	❍	❍	❍
To monitor log-ins by students	❍	❍	❍	❍	❍	❍

To detect student cheating	❍	❍	❍	❍	❍	❍
To monitor students' time spent in the course	❍	❍	❍	❍	❍	❍
As an early-alert system to determine students at risk	❍	❍	❍	❍	❍	❍
To manage student engagement in the course	❍	❍	❍	❍	❍	❍
To assess patterns of student learning management usage and	❍	❍	❍	❍	❍	❍

non-usage periods						
To assess mean/standard deviation of students' test scores	❍	❍	❍	❍	❍	❍
For instructional management - dropping students for non-participation	❍	❍	❍	❍	❍	❍
For instructional management - to determine student progression within the course	❍	❍	❍	❍	❍	❍

To provide intervention	❍	❍	❍	❍	❍	❍
Measure learning outcomes and goals	❍	❍	❍	❍	❍	❍
Analyze trends	❍	❍	❍	❍	❍	❍
To reflect upon and enhance my own teaching practice	❍	❍	❍	❍	❍	❍
To improve retention in my courses	❍	❍	❍	❍	❍	❍
For research purposes	❍	❍	❍	❍	❍	❍

Q12 Are there any other areas not specified in the previous questions/s in which you are using learning analytics? If so, please explain.

Q13 If you PREVIOUSLY used learning analytics, but you are NO LONGER using them, please tell us why by checking the box(es) below.

	I experienced this
I didn't think it was worth investing my time nor talent.	❑
My supervisor/college/university encouraged the use of learning analytics but since then I discontinued using them.	❑
My learning management system doesn't offer learning analytics.	❑
I don't use a learning management system with any of my courses.	❑
I don't know how to use learning analytics.	❑
I have never received training on the use of learning analytics.	❑
My college/university doesn't offer campus assistance for those using learning analytics.	❑

My college/university doesn't offer professional development incentives to learn analytics.	❑
I do not believe learning analytics altered my method of teaching.	❑
I do not believe learning analytics would enhance student learning in my courses.	❑
I do not believe the statistics in learning analytics are accurate.	❑
Privacy issues	❑
Learning analytics are too complicated.	❑
I don't have the time to use learning analytics.	❑
It is too difficult to learn analytics.	❑
My colleague(s) used learning analytics and didn't find them to be useful.	❑
It is not a part of my institution's culture.	❑
It diverts time from my current research.	❑
It diverts time from my teaching.	❑
It is an imposition.	❑

There is no relative advantage	❑
There are no incentives for me to use them.	❑
I am no longer teaching	❑
I do not have the pedagogical expertise to make meaningful use of learning analytics.	❑
Cost and problems of building a course in an LMS	❑

Q14 If you have NEVER used learning analytics, please tell us why by checking the box(es) below.

	This is why I have never used learning analytics
Until today, I have never heard of learning analytics.	❍
My learning management system doesn't offer them.	❍
I didn't think it was worth investing my time nor talent.	❍

My supervisor/college/university encouraged the use of learning analytics but since then I discontinued using them.	❍
I don't use a learning management system with any of my courses.	❍
I don't know how to use learning analytics.	❍
I have never received training in the use of learning analytics.	❍
My college/university doesn't offer technical support for those using learning analytics.	❍
My college/university doesn't offer professional development incentives to learn analytics.	❍
I do not believe learning analytics would alter my method of teaching.	❍
I do not believe learning analytics would enhance student learning in my courses.	❍
I do not believe the statistics in learning analytics are accurate.	❍
Privacy issues.	❍

Learning analytics are too complicated.	❍
I don't have the time to use learning analytics.	❍
It is too difficult to learn analytics.	❍
My colleague(s) used learning analytics and didn't find them to be useful.	❍
It is not a part of my institution's culture.	❍
It diverts time from my current research.	❍
It diverts time from my teaching practices.	❍
It is an imposition.	❍
There is no relative advantage.	❍
There are no incentives for me to use them.	❍
I did not believe it is pedagogically sound.	❍
I do not have the pedagogical expertise to make meaningful use of learning analytics.	❍

Q15 If you have used learning analytics, what challenges have you faced while using learning analytics in the courses you have taught? If you have never used learning analytics, please leave this box empty.

Q16 Please click the little arrows below on the right to finalize and submit your answers. Thank you for completing this survey. Your responses are greatly appreciated.

Appendix B

Interview of Current Learning Analytics Practices

The following interview is being administered to a judgment sample (or expert choice sample(e), in which the researcher has identified you as a representative example of current faculty use of learning analytics at your higher institution of learning. This addendum will be added to your previous survey. Your additional answers to these questions will help guide a phenomenological study of learning analytics to provide a more robust description or "lived experience" of how learning analytics are actually being used in higher education. This is a research project conducted by Kendall Hartley, Associate Professor of Educational Technology and Janet King a PhD student at UNLV. You are invited to participate in this research project because you teach courses or have taught courses in an institution of higher education in the past 5 years.

Your participation in this research study is voluntary. If you decide to participate in this research interview, you may withdraw at any time.

The interview that will take approximately 30 minutes. Your responses will be confidential and we do not collect identifying information such as your name, email address or IP address.

If you have any questions about the research study, please contact Janet King at 702 406 5558. Research has been reviewed according to UNLV IRB procedures for research involving human subjects.

1) Can you please describe as detailed as possible a special situation in which you have used learning analytics in your practice of teaching at your institution of higher learning?
2) How do you believe your use of learning analytics will change in your near future?
3) Do you believe your use of learning analytics helps students? Please explain.
4) What, if any, are the mitigating factors influencing your use of learning analytics?
5) Do you believe the use of analytic tools in your teaching practice is worthwhile? Please explain.

Appendix C

Emailed Confirmation of Affirmation to Conduct Research

Peter Felten
to me

Sep 18 (3 days ago)

Hi Janet,

Thanks for your patience. The Board met last week and confirmed that we'd be happy to have you be part of the conference, based on the agreements we discussed. Specifically, you will register for the conference and we will provide you with a table/chair at a convenient place for you to informally gather responses from ISSOTL registrants. You won't do anything like put fliers about your research on every chair/table at a plenary event, and we won't plug your research during any plenaries – but you are welcome to be as social and network as much as possible.

OK?

After you register for the conference, please send me a note that this is a go – and I'll start the process of getting you a table/chair.

Best,
Peter

Appendix D

Informed Consent

INFORMED CONSENT

Department of Education

TITLE OF STUDY: Faculty use of Learning Analytics

INVESTIGATOR(S): Dr. Hartley and Janet King

For questions or concerns about the study, you may contact Janet King at **7024065558.**

For questions regarding the rights of research subjects, any complaints or comments regarding the manner in which the study is being conducted, contact **the UNLV Office of Research Integrity – Human Subjects at 702-895-2794, toll free at 877-895-2794 or via email at IRB@unlv.edu.**

Purpose of the Study

You are invited to participate in a research study. The purpose of these study is the faculty use of learning analytics in their teaching practice.

Participants

You are being asked to participate in the study because you fit this criteria: taught courses in higher education during the past five years.

Procedures

If you volunteer to participate in this study, you will be asked to do the following: complete a survey. Expert interview of 3 to 10 participants consisting of five questions if respondent has advanced use of learning analytics in their teaching practice.

<u>Benefits of Participation</u>
There will not be direct benefits to you as a participant in this study. However, we hope to learn information about the extent and nature of faculty use of learning analytics that will fill a gap in the literature on this topic.

<u>Risks of Participation</u>
There are risks involved in all research studies. This study may include only minimal risks. *State the level of anticipated risks (i.e. you may become uncomfortable when answering some questions).*

<u>There is no anticipated risk as the questionnaire has non-threatening questions. The only discomfort is the time spent in the survey or the interview.</u>

<u>Cost /Compensation</u>

There is a cost of $250 plus travel costs to attend the conference where the research will be conducted. This is the only financial cost to participate in this study. The study will take 3 days of time. You will not be compensated for my time.

<u>Confidentiality</u>

All information gathered in this study will be kept as confidential as possible. No reference will be made in written or oral materials that could link you to this study. All records will be stored in a locked facility at UNLV for 3 years after completion of the study. After the storage time the information gathered will be permanently destroyed.

<u>Voluntary Participation</u>

Your participation in this study is voluntary. You may refuse to participate in this study or in any part of this study. You may withdraw at any time without prejudice to your relations with UNLV. You are encouraged to ask questions about this study at the beginning or any time during the research study.

<u>Participant Consent:</u>

I have read the above information and agree to participate in this study. I have been able to ask questions about the research study. I am at least 18 years of age. A copy of this form has been given to me.

Signature of Participant Date

Participant Name (Please Print)

Audio/Video Taping:

I agree to be audio or video taped for the purpose of this research study.

Signature of Participant Date

Participant Name (Please Print)

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Curriculum Vitae
Resume — Janet King

Curriculum and Instruction, Teaching and Learning

Educational Technology—UNLV PhD

Master of Science—Sociology

Certified to teach Sociology, Psychology, Political Science and Education

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Over 25 years -Experience in education with exceptional skills, including:
HTML – ePortfolio—Blackboard Learn—Instructional Design—Webpage Construction – Office Suite—-Adobe Suite, Mobile Technology— Smart Classroom Technology— Camtasia— Respondus – Camtasia – Audacity – D2L – Publisher – Garageband – Google Products—Word Press—Learning Analytics

Education

University of Nevada Las Vegas, Completing PhD in Educational Technology, ABD

Mississippi State University, MS, Sociology (major) 1986

University of North Alabama, BS, Majors in Sociology and Political Science, 1984

Northern Arizona University, 1987 - 1991, 15 post-graduate hours in Psychology

Arizona State University, 1991, 9 post-graduate hours in Psychology

University of Alabama in Huntsville, 2001, 3 post-graduate hours in Psychology

University of Nevada, Reno and Las Vegas, 21 post-graduate hours in Psychology

Employment at Nevada System of Higher Education

CSN—Senior Analyst for e-Learning; Adjunct Instructor

University of Nevada Las Vegas, Graduate Assistant, Teaching and Learning, CIT 667, EDU 214, CIL 652
Western Nevada College, Fallon, NV, Instructor Sociology and Psychology

Previous Employment:

Maricopa Community College District and Eastern Arizona College, 1988 – 2006 (taught various semesters throughout this range), Adjunct Instructor of Sociology at Maricopa and Full Time Instructor of Sociology at EAC (Chair of Sociology), 2411 W. 14th St., Tempe, AZ 85281, (480) 731-8465

Calhoun Community College and Faulkner University, PO Box 2216, Decatur, AL 35609 and 5345 Atlanta Hwy, Montgomery, AL 36109, 2001 - 2002, Adjunct Sociology (256) 306-2500 and (334) 272 5820

Mississippi Agriculture and Forestry Experiment Station at Mississippi State University, Research assistant—1985 – 1986

Chattanooga State Community College, Chattanooga TN, Instructor of Psychology & Sociology, Dual Enrollment Program.

Awards and Accomplishments:

2007: Founded Helping Professions Scholarship; First Place Coalition for Literacy

2008: Third Place Photography Contest CCC Communications

2008: Founded Boys and Girls Club Scholarship

First Place Photography Contest CCC Communications
2009: Photojournalist for Educause 2009 Conference in Denver
Founded Boys and Girls Club Scholarship
2009: Presented seminar on web-based learning at Cengage Survival Camp, San Antonio, TX, Elected Secretary of the Board for the Boys and Girls Club of Mason Valley
2009: Received two awards for scholarship contributions
2009: Received Cantaloupe Festival Parade Outstanding Group Award
2009: Elected to State Democratic Executive Committee representing Churchill County
Presented seminar– online learning at National Institute for Teaching Psychology, Peer assessment at Nevada Assessment Conference, presented a 4-hour workshop on building online classes at Society for Personality and Social Psychology, Las Vegas
2010: Keynote Speaker- two California conferences, San Joaquin Valley College
New Mexico High Education Assessment Conference
2011: 4-hour workshop building online classes at Society for Personality & Social Psychology

2013-14: Presented at numerous Cape Sessions and Convocations; HighEdWeb Annual Conference, presenter
2014: Las Vegas CSN Adjunct Conference, presenter; Digital Conference, presenter
2014: Nominated for NSHE Creative Activities Award
2015: Nominated for 2015 Campus Technology Innovator Award
ITC Conference—Two Presentations on Course Analytics and Social Networking; SITE Conference— Presentation on Course Analytics; AACC Conference—Presentation on Course Analytics
2015: College of Southern Nevada Woman of Influence Award
2017: UNLV 2017 Outstanding Graduate Award

Past and/or Present Professional Membership

American Sociological Association -Rural Sociological Society -American Psychological Association - Alabama-Mississippi Sociological Association -Mid-South Sociological Association- Southern Sociological Association—International Society for the Scholarship of Teaching and Learning - Society for Personality and Social Psychology - National Institute for Teaching Psychology - Pacific Sociological Association—HighEdWeb– Instructional Technology Council -AACC

College and Committee Affiliations:

Program and Assessment Review Committee; Bylaws & Rules Committee
Curriculum Committee; Environmental Strategies Committee; Giving Committee (Co-Chair); Scholarship Committee; Articulation Committee NSHE