Identifying Critical Factors That Impact Learning Analytics Adoption by Higher Education Faculty

By

Michael Knupp

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Student Name: Michael Knupp

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Dissertation Chair/Co-Chair: DocuSigned by: [signature] E0CE171C3CDE419... Date: 04/10/2024
Print Name: Dr. Jun Liu

Dissertation Chair/Co-Chair: ______________ Date: ______
Print Name: ______________

Committee Member: DocuSigned by: Dr. Insu Park AD181583719C41C... Date: 04/10/2024
Print Name: Dr. Insu Park

Committee Member: DocuSigned by: Dr. Mark Hawkes 021B457BCCBB4AC... Date: 04/10/2024
Print Name: Dr. Mark Hawkes

Committee Member: DocuSigned by: Dr. Yong Wang 79AB505BC7B649E... Date: 04/10/2024
Print Name: Dr. Yong Wang

Committee Member: ______________ Date: ______
Print Name: ______________

Abstract

Higher education institutions (HEI) are beginning to invest heavily in learning analytics as a compliment to their existing suite of technologies used to enhance the pedagogical practices of instructors. However, learning analytics continues to see low adoption and integration by higher education faculty. While a culture of learning analytics within HEI is emerging, there is not consensus on the value and effectiveness of the tools and practices that make up the culture. With promises of reduced student dropout rates, improved student outcomes, better course pedagogy and backed by pressures of assessment and accountability, learning analytics is being trumpeted as the next best solution to our educational woes. However, despite these promises, and despite the general belief that learning analytics may have true value, instructors have been slow, if not resistant, in learning analytics adoption. More research is needed to understand factors that either threaten or enable a higher education faculty member’s willingness to adopt learning analytics. The following paper demonstrates how the technology-pedagogy-content knowledge framework (TPACK) can be used to extend traditional technology adoption models to include professional identity expectancy in an effort to explain intention to use behavior. A quantitative analysis using SEM techniques on 222 United States based survey respondents is used to inform results. The results support effort expectancy, performance expectancy, and professional identity expectancy to be key factors of willingness to adopt learning analytics. These results may inform additional research into the influence of professional identity expectancy on technology adoption as well as research, development, and marketing opportunities within the consumer space of learning analytics tools.

Keywords: analytics culture, data analytics, higher education institutions, learning analytics, learning analytics adoption, professional identity, technology adoption, TPACK

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Chapter 1. Introduction

A data revolution is upon us. For-profit businesses have successfully capitalized on using vast amounts of data and sophisticated analytical tools to drive huge profits and tremendous market share (Thirathon, Wieder, Matolcsy, & Ossimitz, 2017; Davenport, 2006; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Choo, et al., 2006). It is clear that organizations, as they always have, seek to make good strategic and operational decisions. However, the processes and tools available to make these decisions is rapidly changing. Organizations are beginning to adopt a culture of analytics (Gupta & George, 2016) and it becomes an interesting challenge to understand where higher education institutions (HEI) stand in this landscape.

HEIs are interesting organizations to study due to the relatively new exploration of analytics and the wide diversity of the analytics being used (Avella, Kebritchi, Nunn, & Kanai, 2016). Approximately ten years ago a call to arms was put forth to HEIs to migrate beyond traditional uses of analytics in management of enrollment, retention and alumni relations and explore the integration of analytics in the pure academic and learning space (Campbell, Deblois, & Oblinger, 2007). Early exploration of this space pushed HEIs to invest in analytics that provided true measurement of institutional goals (Norris, Baer, Leonard, Pugliese, & Lefrere, 2008). HEIs don't only use analytics to improve revenue or profit margins (traditionally viewed as business analytics), they also use analytics within the curriculum landscape (Norris, Baer, Leonard, Pugliese, & Lefrere, 2008). It is within the curriculum landscape where things get interesting as the broad field of analytics narrows to learning analytics (LA). In the ensuing years, the field of learning analytics begins to take shape. The first annual international conference in learning analytics and knowledge was held in 2010. The first edition of the Journal of Learning Analytics was published in 2013. In the inaugural issue, Seimens (2014) points out that higher education is comparatively late to the analytics game but their presence is important as data continues to play a key role in how learning transpires and how faculty make decisions within the learning context. While a multitude of different definitions of learning analytics have evolved over the years, the definition provided at the inaugural international conference on Learning Analytics in 2011 provides a sound base (Siemens, Long, Gasevic, & Conole, 2010): *"The measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and environments in which it occurs."* (p. 1). The use of the word 'optimizing' is noteworthy. Learning analytics imparts an economic lens on the educational process. It is possible that this economic lens may run orthogonal to an instructor's traditional view of education and to their own professional identity. Such a belief may influence a higher education faculty member's willingness to adopt learning analytics into their pedagogical practices. LA research conducted to date has primarily focused on LA design (Bakharia, et al., 2016; Greller & Drachsler, 2012), data visualization design (Echeverria, et al., 2018), or use cases that support using LA as a retention or early warning system (Gasevic, Dawson, & Siemens, 2015). Literature reviews in LA also show emerging concerns over data ownership, privacy, and ethics (Avella, Kebritchi, Nunn, & Kanai, 2016; Tsai, Kovanovic, & Gasevic, 2021; Viberg, Hatakka, Balter, & Mavroudi, 2018). While there exists a generally shared belief in the positive impact and potential of learning analytics, institutions and individual faculty show surprisingly slow (perhaps even resistant) adoption rates (Alzahrani, et al., 2023; Herodotou, et al., 2017). Determining factors that influence this resilience poses an interesting research challenge. An important perspective is that LA represents a disruptive influence on the current culture in higher education institutions (Avella, Kebritchi, Nunn, & Kanai, 2016). LA push the barriers of accountability and assessment (Sergis & Sampson, 2017). While prior LA research projects point to the importance of the stakeholders and specifically the individual faculty member (Campbell, Deblois, & Oblinger, 2007), a research gap exists as it pertains to the perspective of the individual faculty member. Campbell, et al., (2007) specifically point to the importance of faculty in the process of utilizing learning analytics, *"Faculty are key to "interventions" ... For some faculty, analytics may provide a valuable insight into which students are struggling or which instructional approaches are making the greatest impact."* (p. 54). The faculty perspective gap opens an opportunity for further study. Specifically, it becomes interesting to explore the various personal and organizational constructs that affect the willingness of a higher education faculty member to adopt LA. The existing body of LA does not sufficiently represent the perspective of the higher faculty member. This perspective is critical in understanding how various constructs may threaten or enable willingness to adopt LA.

Statement of the Problem

An emergent phenomenon exists within higher education institutions. HEIs are slowly adopting a culture of LA but there is not consensus on the value and effectiveness of the tools and practices that make up the culture. There exists tremendous variability in how individual faculty members interface with LA as it relates to adoption, sense making, and influence on professional identity (Avella, Kebritchi, Nunn, & Kanai, 2016). A demand for more research to understand the beliefs of users of the LA systems exists (Ferguson, et al., 2016). Ferguson, et al. (2016) specifically offer five different important questions that provide an appropriate starting point for the proposed research (p. 34):

Q1: How do people behave when learning analytics initiatives are undertaken?

Q2: What is the current state of awareness, acceptance, and beliefs about applying analytics to teaching and learning?

Q3: How are analytics perceived in terms of usefulness and relevance?

Q4: How significant are differences in regional or sector culture, values, and professional practice, in relation to implementing learning analytics?

Q5: Which norms of professional practice, power, and influence do learning analytics challenge?

These questions are a foundational starting point and can be viewed through the lens of willingness to adopt. An important research agenda is to better understand key constructs that serve to enable an individual higher education faculty member to be willing to adopt LA into their daily practice. LA in part is just one of the latest manifestations of new technologies. Most LA are embedded into existing learning management systems which are already adopted on a very large scale. Given that LA is just a different flavor of technology, it is easy to assume that existing technology adoption models will seamlessly apply. In places this is likely to be the case. But LA have characteristics which differentiates itself from other typical educational technology. First, LA is not a standalone device like a graphing calculator or an interactive smartboard. It is not just one technology, but an amalgamation of many technologies. Second, there is an inherent feedback loop incorporated into the design of LA. LA are intended to evaluate a given pedagogical experience, transparently report on that experience, and then be interpreted by the stakeholders in the pedagogical experience in order to inform the future direction of the experience. And lastly, LA focus multiple aspects of pedagogy that most educational technologies do not. Specifically, LA brings into focus technical knowledge, pedagogical knowledge and discipline or content knowledge. LA, like any analytics, should make the professional environment better, not worse. A culture of LA may have negative, unintended consequences on key stakeholders. A failure to recognize these consequences could contribute to continued poor LA adoption that in turn could limit the future evolution of educational systems. The LA research corpus lacks research placing the higher education faculty stakeholder front and center. Certainly, faculty buy-in plays a large role in LA adoption (Dawson, et al., 2018). The implications of the research can potentially aid practitioners by uncovering key constructs of how an LA culture influences their willingness to adopt. This guides the following fundamental research questions.

> RQ1: What are the emergent enablers to a higher education faculty member’s willingness to adopt learning analytics into their professional practice?
>
> RQ2: What role does the concept of professional identity expectancy fill in determining a higher education faculty member’s willingness to adopt learning analytics?

The purpose of this quantitative theory testing study is to examine how extent technology adoption theory models may be adjusted to incorporate the influence of professional identity into the specific adoption of LA. Additionally, the study is intended to more clearly understand the enablers that exert a positive influence on the willingness of fulltime higher education faculty to adopt LA into their professional practice. Of particular research interest is fulltime faculty that teach courses at universities that offer traditional two year associate degrees, four year bachelor degrees, or advanced professional level doctorate degrees. The proposed research study seeks to fill a gap in the LA research literature as it pertains to adoption and perceptions of learning analytics from higher education faculty. The proposed research also seeks to serve the practitioner community by offering insight into challenges and opportunities of LA usage and adoption within higher education institutions.

Theoretical Foundation

On the surface, the emergent culture of LA in higher education represents significant change to extent educational culture. However, technology integration pushes the education domain to be in a constant state of change. The true underlying issues with LA in higher education is adoption and integration. Similar research that focuses on the phenomenon of learning management system integration within secondary schools (Towne, 2018), reveals several theories applicable to this research. The phenomenon of LA usage by higher education faculty in part represents an example of technology adoption. As such, theories such as the technology adoption model (TAM) (Davis F. , 1989) or the unified theory of acceptance and use of technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) provide a good base. While TAM and UTAUT are widely used theories, they continue to prove helpful in understanding why certain technologies are adopted and why certain technologies are not. UTAUT represents a potential valuable theory as this theory specifically addresses concepts of performance expectancy, effort expectancy, and social influence. But UTUAT, as an overarching theory base, lacks specificity to the education domain and the perspective of the higher education faculty member. The higher education faculty member is assumed to be a rational actor in the culture of analytics. Psychology based theories such as the theory of reasoned action (TRA) (Sheppard, 1988) or the theory of planned behavior (TPB) (Ajzen, 1991) are reasonable theory bases to draw from. Yet here again, these theories fail to address the unique characteristics of the higher education organization. Cognitive science theories on decision-making such as Rational Choice Theory (Tversky & Kahneman, 1981) were also considered but fell short against the strength of the Technological Pedagogical Content Knowledge Framework (TPACK) (Mishra & Koehler, 2006). Higher education faculty are expected to incorporate new tools and new processes into their day-to-day workflow. Their ability to leverage LA tools and information effectively may hinge in large part on both their self-identified analytical skillsets and their personal beliefs in learning new ways to evaluate student learning. TPACK provides a strong theoretical foundation for examining LA adoption. The TPACK framework serves very well as the theory base for this research. Mishra and Koehler (2006) introduced TPACK in order to provide a stronger theoretical framework for the adoption and usage of educational technology. TPACK seeks to explain the complex interactions of three distinct knowledge areas; technology, pedagogy and content. These interactions exist on a binary level between two distinct knowledge areas and on a multifaceted level where all three knowledge areas come together as one. Using this conceptual framework as a theory base, willingness to adopt can be explored along the same three basic vectors. Technology knowledge can be interpreted as efficacy with learning analytics technologies. Pedagogy knowledge relates to how an individual higher education faculty member reconciles learning analytics against their pedagogical practices. Content knowledge speaks directly to the specific disciplinary knowledge that a faculty member possesses. Content knowledge can be extended to include beliefs about what is required to be a professional within a respective discipline. Lastly, willingness to adopt a certain educational technology can be examined by the manner in which all three forces come together. Research helps to understand the forces that a culture of LA exerts on the higher education faculty member's willingness to adopt. In part, these forces can be examined through the concept of alignment and specifically how the perceptions of LA aligns to the faculty member's efficacy with learning analytics, their pedagogical practices and their professional identity. The TPACK framework is visually depicted in Figure 1 (Koehler, Mishra, & Cain, 2013). The framework establishes seven core knowledge constructs that work in concert with each other to help explain technology integration in education; Technology Knowledge (TK), Content Knowledge (CK), Pedagogy Knowledge (PK), Technology-Content Knowledge (TCK), Technology Pedagogy Knowledge (TPK), Content-Pedagogy Knowledge (CPK) and Technology-Content-Pedagogy Knowledge (TPACK).

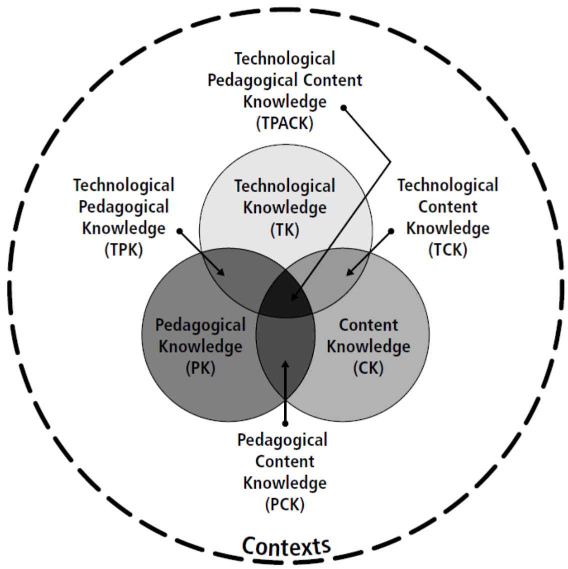


Figure 1. Technological pedagogical content knowledge framework

While technology is a broad based concept, within the confines of this research project, technology is specifically focused on learning analytics. The TPACK framework provides an excellent theory model to understanding the complex interactions between learning analytics efficacy, perceived relative advantages of integrated learning analytics into professional teaching practices and the alignment of learning analytics to professional identity.

Research Model Explanation and Hypotheses

Figure 2 depicts the initial model for the research. This initial model guided the pilot survey. However, data analysis completed on the results of the pilot survey instrument revealed structural issues with the model and overall design limitations with the survey. The pilot survey was revised and a final survey instrument was created and disseminated based on a more appropriate and explanatory research model. The revised research model that guided the initial creation of the final survey is presented in Figure 3.

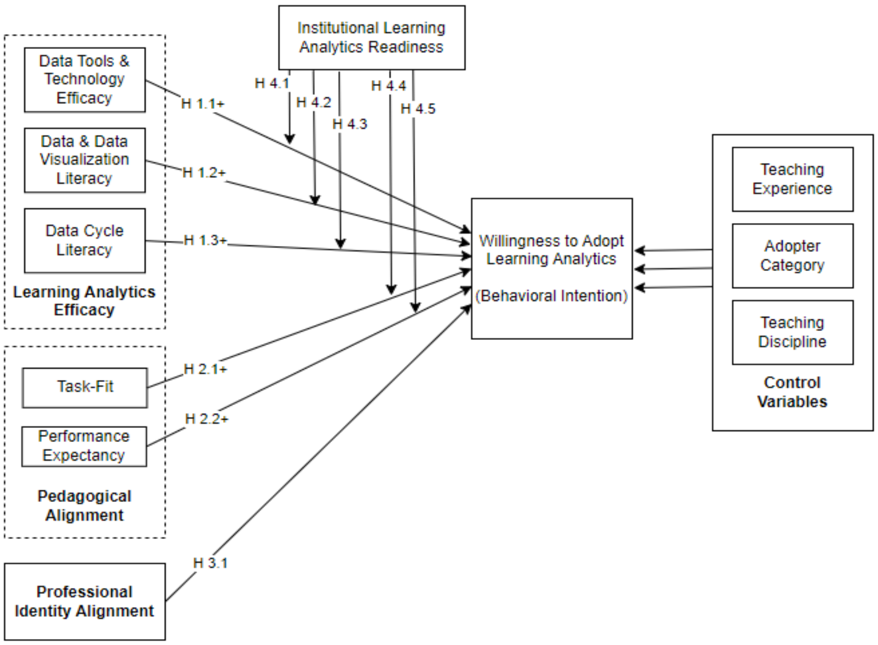


Figure 2. Initial research model that guided the pilot survey

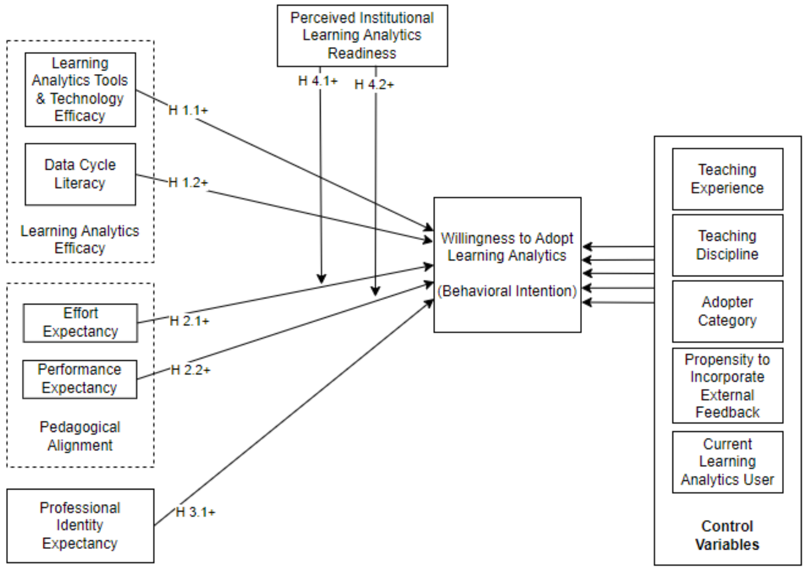


Figure 3. Final hypothesized research model to identify factors that enable LA adoption

Dependent Construct

Willingness to adopt constitutes a behavioral intention. As it applies to behavioral intention, it becomes interesting to investigate differences between hopeful intention and dedicated intention. For example, an individual may be hopeful to win the lottery, but this would not constitute dedicated intention. As it applies to adoption of LA, a higher education faculty member may be hopeful to adopt these technologies in the future, but not highly dedicated to carrying out the required actions to put them into practice. On the other side, a higher education faculty member may carry very strong intentions to incorporate LA into their professional practice. In either case, the faculty member may or may not be a current user of LA. In the end, a single dependent construct exists for the proposed research model.

> Willingness to adopt describes the likelihood that a higher education faculty member hopes or intends to use learning analytics within their day to day pedagogical practices.

Independent Constructs

The independent constructs of the research model focus on the high level concept of LA efficacy and pedagogical alignment. Efficacy is broadly characterized as the ability to create or attain a desired outcome. An individual's skills and knowledge contribute greatly to the perception of their own efficacies. Efficacy plays a key role in the adoption of new technologies (Davis F. , 1986; Venkatesh, Morris, Davis, & Davis, 2003). Alignment characterizes the manner in which distinct concepts reach a state of agreement or alliance. In general, if concept X is in alignment with concept Y, then one can argue that concepts X and Y are in congruence in so much as both share qualities that describe a larger phenomenon or may help to achieve a greater goal. If concept X is not in alignment with concept Y, then one can argue concepts X and Y are not in congruence. And furthermore, the lack of congruence may skew the understanding of a larger phenomenon or negatively impact the realization of a greater goal. Additionally, alignment can be characterized on a spectrum from weak to strong. These two concepts; efficacy and alignment, are at the heart of the independent constructs.

Learning Analytics Efficacy

Effective integration of LA into professional practice requires the higher education faculty member to embody certain knowledge and skills. This is the heart of the TPACK framework (Mishra & Koehler, 2006) used as the theoretical base for this research. The foundational skills and knowledge for LA reside in analytical technologies and tools and data cycle literacy. Dunn, et al., explore data tools and technology as well as data literacy in their research on teacher efficacy and anxiety in the data-driven decision process (Dunn, Airola, Lo, & Garrison, 2013). Efficacy has also played a key role in major technology adoption theories such as TAM and UTAUT (Davis F. , 1986; Venkatesh, Morris, Davis, & Davis, 2003). While efficacy in the tools and technology of LA is important, an understanding of the foundational data life cycle also has value. Clow (2012) envisions the conceptual framework of LA as a cycle depicted in Figure 4. Learners are at the top of this cycle and while a cycle does not technically have a true starting position, the framework assumes learners initiate the LA cycle. Learners create data that is collected, measured and analyzed through metrics. The metrics lead to interventions with learners. In turn, learners create new data and the cycle continues. The central concept of this data model is the existence of an inherent cycle in LA; a built in feedback loop within the teaching-learning process.

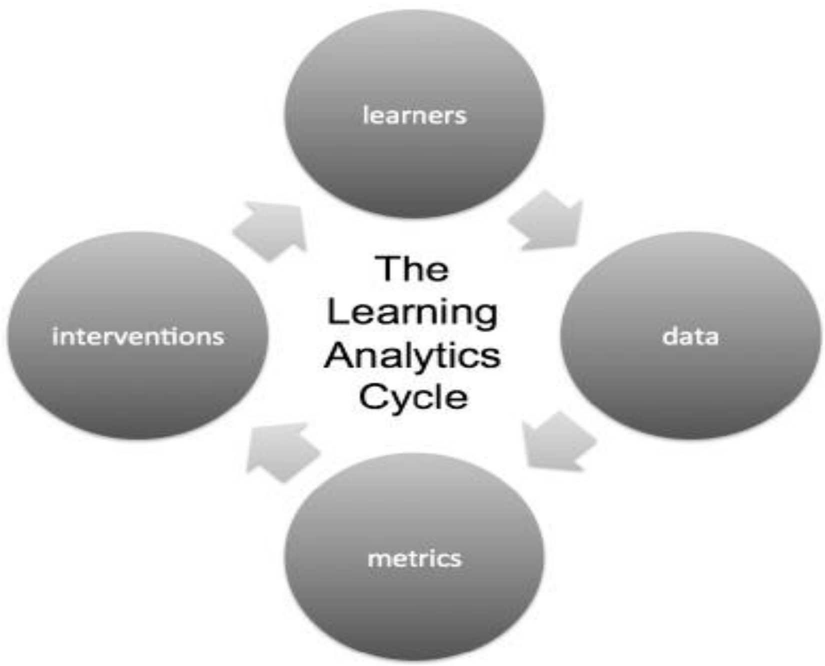


Figure 4. The learning analytics cycle

As such, it is clear that efficacy in these areas contributes to the culture of LA. Efficacy in these areas come together to define LA alignment. As such, the following formal definitions emerge.

Learning Analytics Tools and Technology Efficacy describes the degree to which a higher education faculty member is confident in their ability to interact with and use data systems and tools.

Data Life Cycle Literacy describes the degree to which a higher education faculty member is confident in their understanding of the basic data cycle which includes process steps of data collection and correction, data analysis, interpretation of results and corrective action taken based on results. A process cycle is formed whereby the corrective action leads back to data collection and the cycle repeats itself.

Furthermore, the following are the hypothesized relationships between learning analytics efficacy constructs and willingness to adopt.

H 1.1: The stronger a higher education faculty member perceives their efficacy with learning analytics tools and technology, the more willing they will be to adopt learning analytics into their professional practice.

H 1.2: The stronger a higher education faculty member perceives their literacy with the data cycle, the more willing they will be to adopt learning analytics into their professional practice.

Pedagogical Alignment

Pedagogical alignment describes the degree to which the higher education faculty member perceives the goals and purpose of LA run congruent to their specific pedagogical practices performed in a given instructional setting. Pedagogical alignment can be perceived along two basic constructs; effort expectancy and performance expectancy. The role that effort expectancy plays in technology adoption has roots in Davis's seminal work with the Technology Acceptance

Model and more specifically his investigation into perceived ease of use (Davis F. , 1986). Perceived ease of use is very similar to the concept of task-fit. Task-fit focuses on the degree to which the characteristics of the technology meet the requirements needed to complete the task. Goodhue and Thompson posit the importance of task-technology fit in explaining how an individual's performance may be impacted by the alignment of the task characteristics and the characteristics of the technology (Goodhue & Thompson, 1995). This is a vital element of technology adoption theory with overlaps to compatibility as explored by Moore and Benbasat (Moore & Benbasat, 1991) and to job relevance as detailed in the TAM 3 model (Venkatesh & Bala, Technology Acceptance Model 3 and a Research Agenda on Interventions, 2008). Effort expectancy as an explicit construct was detailed in the UTAUT model (Venkatesh, Morris, Davis, & Davis, 2003). In this model, effort expectancy explains the ease of use of the system as perceived by the individual interacting with the system. Within the LA adoption framework, effort expectancy is defined as the ease of using learning analytics tools and technology as perceived by the higher education faculty member.

Performance Expectancy is the degree to which the higher education faculty member believes that using LA will help them to better achieve their pedagogical goals. Behavioral intention and action are often based on a value proposition. In the original TAM model, the value proposition states intention to use is predicated on the value of ease of use and perceived usefulness (Davis F. , 1986). What is implied here is the user sees value in adopting a system because the system will not only prove to be useful, but the system is also easy to use and thus does not impart a high cognitive load. The value proposition is further explored in the foundational UTAUT model (Venkatesh, Morris, Davis, & Davis, 2003). Here the researchers specifically incorporate performance expectancy into the research model and define the construct as the degree to which the user believes using the system will help them to perform their job. As it pertains to learning analytics, higher education faculty will likely need to see a value proposition for adoption. Performance expectancy speaks directly to this interpreted value proposition. The alignment of the learning analytics technology to pedagogical tasks is an important element of the model and as such, the following definitions emerge.

> Pedagogical Alignment is an umbrella term that describes the degree to which the higher education faculty member perceives the goals and purpose of learning analytics complement their specific pedagogical needs and practices. Alignment is achieved through the interaction of effort expectancy and performance expectancy.
>
> Effort Expectancy describes the degree to which the higher education faculty member perceives the learning analytics tools and related technologies easy to use and easy to incorporate into their specific pedagogical practices performed in a given instructional setting.
>
> Performance Expectancy is the degree to which the higher education faculty member believes that using learning analytics will help them to better achieve their pedagogical goals.

Based on these definitions, the following relationships are hypothesized.

> H 2.1: The higher the effort expectancy (ease of use) as perceived by the higher education faculty member, the more willing they will be to adopt learning analytics into their professional practice.
>
> H 2.2: The higher the performance expectancy as perceived by the higher education faculty member, the more willing they will be to adopt learning analytics into their professional practice.

Professional Identity Alignment

The multi-faceted nature of professional identity results in a difficulty establishing a strict definition (Trede, Macklin, & Bridges, 2012). But the research does purport elements of attitude, beliefs and standards that are consistent with one's primary area of profession. Professional identity is an important area of study (Barbour & Lammers, 2015) and certainly within education (Day, Kington, Stobart, & Sammons, 2006; Barbara-i-Molinero, Cascon-Pereira, & Hernandez-Lara, 2017; Trede, Macklin, & Bridges, 2012; Haamer, Lepp, & Reva, 2012). However, professional identity has not been an area of study within traditional technology adoption research. Trede et al., (Trede, Macklin, & Bridges, 2012) specifically point to the importance of professional identity and how professional identity shapes practice, *"All point towards the notion that professional identity is a way of being and a lens to evaluate, learn and make sense of practice."* (p. 375). If professional identity is truly a lens for how one approaches their professional practice, there is a strong possibility that it plays an important role in adopting technologies. Teachers tend to have a very strong professional identity as teaching can tend to be more of something you are versus something you do (Korthgen, 2004). Given this, the following definition emerges and the resulting hypothesis is presented.

> <u>Professional Identity Expectancy</u> is characterized by the degree to which a higher education faculty member perceives (expects) the goals and purpose of learning analytics to align with their perception of their own professional identity.

H 3.1: The higher the professional identity expectancy as perceived by the higher education faculty member, the more willing they will be to adopt learning analytics into their professional practice.

Interaction Construct

An institution's culture with LA and their infrastructural footprint to support learning analytics are important elements of the landscape of learning analytics adoption (Ferguson, et al., 2016; Lismont, Vanthienen, Baesens, & Lemahieu, 2017). A very primitive overall data culture of an organization is evidenced by lack of leadership support for data driven decision making, limited resources for training or lack of incentives for using data and analytical processes. Such a culture likely creates an environment that doesn't foster a willingness to adopt LA. Furthermore, it seems reasonable to assume that a higher education institution that does not possess a technical infrastructure to support LA, does not create an environment that fosters a willingness to adopt learning analytics. For example, lack of an appropriate learning management systems (LMS), limited or silo databases of student and course information, and limited to no support of add-on LMS analytics packages may likely influence willingness to adopt. Therefore, perceived LA readiness factors found in the current organizational culture are hypothesized to have an interaction effect on the relationships between two independent constructs; namely effort expectancy and performance expectancy, and the dependent construct of willingness to adopt learning analytics. The interaction effect is hypothesized to be moderating. The primary stakeholder in this research is the higher education faculty member and as such, it is their perception of the institution's LA readiness factors that are of concern. The perceived readiness construct is specifically defined as follows.

Perceived Institutional Learning Analytics Readiness describes the degree to which a higher education faculty member believes their institution embodies a data centric culture that supports critical learning analytics readiness factors in technical infrastructure, executive sponsorship, faculty development and data driven culture.

From this definition, the following moderating interaction relationships are hypothesized.

H 4.1: Perceived institutional learning analytics readiness will moderate the relationship between effort expectancy and willingness to adopt. The moderated relationship is hypothesized to strengthen the relationship such that the higher the perceived institutional learning analytics readiness, the stronger the effect will be on willingness to adopt.

H 4.2: Perceived institutional learning analytics readiness will moderate the relationship between performance expectancy and willingness to adopt. The moderated relationship is hypothesized to strengthen the relationship such that the higher the perceived institutional learning analytics readiness, the stronger the effect will be on willingness to adopt.

Control Variables

There are several control variables included in the model. The control variables are assumed to influence the behavioral intention dependent construct, but they are not explicitly operationalized through the independent constructs.

Teaching Experience is defined by the number of years of teaching experience binned into the following categories; Limited Experience (0-3 years), Modest Experience (3-10 years), Highly Experienced (10+ years).

Teaching Discipline is the major content area of focus for the higher educational faculty member. Content areas include business, humanities, natural sciences, social sciences, information technology, data science and other.

Adopter Category is defined by how higher education faculty members label themselves within the framework of technology adoption diffusion of innovation theory. The following segment labels are available and leveraged from Roger's work in diffusion of innovation (Rogers, 1983); Innovators, Early Adopters, Early Majority, Late Majority and Laggard.

Propensity to Incorporate External Feedback is a binary measurement indicating if the higher education faculty member tends to utilize traditional feedback, such as student reviews, to improve their pedagogical practices.

Current Learning Analytics User is a binary measurement indicating if the higher education faculty member currently incorporates learning analytics into their professional practice of teaching.

Summary

Chapter 1 provided an introduction to the current state of learning analytics adoption and the basic problem statement. The problem statement of poor adoption rates lends itself to the foundational research question of what promotes or inhibits a higher education faculty member from being willing to adopt learning analytics into their professional practice. A research model based on extant technology adoption theory and TPACK was described and serves to help answer the two specific research questions documented.

Chapter 2. Review of the Literature

In accordance with the focus of research, the literature review focuses in the main areas that support hypotheses generation required to build the theoretical model. The literature review initially provides background on the composition and culture of LA that helps to inform the role that technical efficacy plays adoption behavior. From that, a specific review of the extent technology adoptions models and LA adoption trends is provided. The review of technology and LA adoption builds evidence for the value of the research as well as to inform the inclusion of effort expectancy and performance expectancy in the theoretical model. A review of the literature as it applies to the organizational culture of LA implementation helps to inform the inclusion of perceived institutional readiness in the theoretical model. The traditional technology adoption models are extended in this research through the consideration of professional identity expectancy. The literature search in professional identity localizes to key constructs, descriptions of educator's professional identity and research on the stability vs. volatility of professional identity. This line of review is provided in the professional identity literature review section that follows the technology adoption review. Lastly, the overarching theoretical base for the research is provided in the final section where the evolution and applicability of TPACK to LA adoption is provided.

Composition and Culture of Learning Analytics

While LA is still perceived to be in its infancy, the underpinnings date back to the early 1900s (Joksimovic, Kovanovic, & Dawson, 2019). These underpinnings include work in cognitive science, psychometric exploration, and the learning sciences. However, LA as a true discipline starts to take shape in 2010s with the founding of the Educational Data Mining Society, the founding of the Society for Learning Analytics and Research, the establishment of the Learning Analytics and Knowledge Conference and the first publication of the Journal for Learning Analytics (Joksimovic, Kovanovic, & Dawson, 2019). LA are often characterized as a multidimensional discipline that highly leverage other fields such as research methods, learning sciences, data mining, information science, data visualization and psychology (Gasevic, Dawson, & Siemens, 2015). LA differentiates from other closely related fields of educational data mining, academic analytics and teaching analytics. Educational data mining is a rather broad term, and as a process, carries the high-level goal of making discoveries from the data collected in educational settings (Avella, Kebritchi, Nunn, & Kanai, 2016). The domain of LA differs from academic analytics by focusing on the core-learning context instead of at the institutional level (Jorno & Gynther, 2018). Academic analytics at the institutional level primarily focus on areas such as enrollment management, retention management and donor management (Campbell, Deblois, & Oblinger, 2007; Greer, Thompson, Banow, & Frost, 2016). Teaching analytics aid faculty in effective course design and delivery (Siemens, 2014). LA are deeply entrenched in the learning space that occurs in courses delivered by faculty to students. In the early years, the main objective of LA systems was an early alert system to identify students at risk. Research ensued on the effectiveness of such systems (Greer, Thompson, Banow, & Frost, 2016). Also seen in the early years is an important research project that focuses on stakeholders of LA systems (Draschler & Greller, 2012). It comes as no surprise that students and faculty are the main stakeholders in the LA systems as they have the most to gain from usage of the system. An important result of this study shows that students do not believe they have the necessary competences to independently learn from the information provided by LA. However, the same question was not proposed to the faculty participants in the study.

Barneveld & Campbell (2012) argue that learning analytics is a process that utilizes analytic techniques to support attainment of learning goals. Others argue that learning analytics is about tailoring the educational setting to specific needs and abilities of the individual learner (Avella, Kebritchi, Nunn, & Kanai, 2016). The literature supports the difficulty in applying an exact definition to LA. However, the central tenant running through all working definitions is LA encompass data, tools, methods, stakeholders, systems and policies all focused in the context of a learning environment working to understand and best facilitate the process of learning. As researchers have grappled with understanding LA and their implementations and usage, several key research streams emerge.

There exists a myriad of different research streams within the field of LA. As the corpus of research articles in LA has become larger, literature reviews garner more attention.

Several literature reviews extract more of the "who" and the "what" of LA in the form of a current state (Dawson, Gasevic, Siemens, & Joksimovic, 2014; Viberg, Hatakka, Balter, & Mavroudi, 2018). The general findings of such reviews are that published works tend to be descriptive and case study focused. The reviews also show that research generally lacks strong theoretical backgrounds and as such tends to be more conceptual than empirical. Also highlighted in such reviews is that LA seem to over deliver on promise of potential and under deliver on effectiveness. Ferguson & Clow (2017) add additional support to this phenomenon and specifically offer a solution through the Learning Analytics Community Exchange project named Evidence Hub. The Evidence Hub provides a common space for educators to document where and how the use of LA has had demonstrable positive impact. As LA continues to mature, implementation occurs in very specific situations; such as computer programming courses. Ihantola et al. (2015) review seventy-six different articles and conclude that most studies take place in individual courses, are point in time and not longitudinal and few are grounded in theory. An interesting outcome of the review is an RAP taxonomy for the papers reviewed. RAP deals with the extent to which the original research can be re-analyzed (R), extend the original analysis using different methods or tools (A), and repeatability of the original analysis process with new data (P). The net conclusion is that most LA studies in computer programming are extremely difficult to replicate.

Sergis & Sampson (2017) focus their literature review on the intersection of LA and teaching analytics. They differentiate the two by arguing that teaching analytics focus on course design and LA focus on learners and the learning context. They further advocate a consolidation of the two for analytics in the educational space to reach its true potential. Multiple literature reviews concentrate on the methods, challenges and benefits of LA (Avella, Kebritchi, Nunn, & Kanai, 2016; Leitner, Khali, & Ebner, 2017). Avella highlights that LA utilize methods such as visual data analysis, social network analysis, prediction, clustering and relationship mining. The bricolage nature of LA shows itself with these methodologies as the methods are adopted from traditional educational data mining techniques. Avella's literature search also reveals numerous perceived benefits of the usage of LA: improved student learning outcomes, personalized learning and improved instructor performance. Balancing against these perceived benefits are challenges of how to truly optimize the learning environment, appropriately analyze the analytics and issues with ethical use and data privacy. Other work points to available time to work with LA and lack of consistent culture as challenges (Leitner, Khali, & Ebner, 2017). Overall, the literature reviews in LA show that the field is strong and an area of interest for many researchers and practitioners. The reviews highlight issues with grounding LA in theory and unrealized potential. The reviews also highlight the complexity of the emerging domain. Higher education faculty that do not possess confidence in understanding the underpinnings of this emergent domain may be less willing to adopt LA. Perhaps in an effort to ground LA more in theory, researchers offer many conceptual frameworks for LA system design and culture. These conceptual frameworks are the focus of the second key LA research stream.

The conceptual framework offered in Figure 5 emphasizes the teacher as the core component and stakeholder to learning analytics design (Bakharia, et al., 2016). This model incorporates pedagogical intent. The teacher must process the various types of analytics within a given context in order to determine an appropriate course of action. This framework highlights the dual context of learning and teaching as these are two distinct processes.

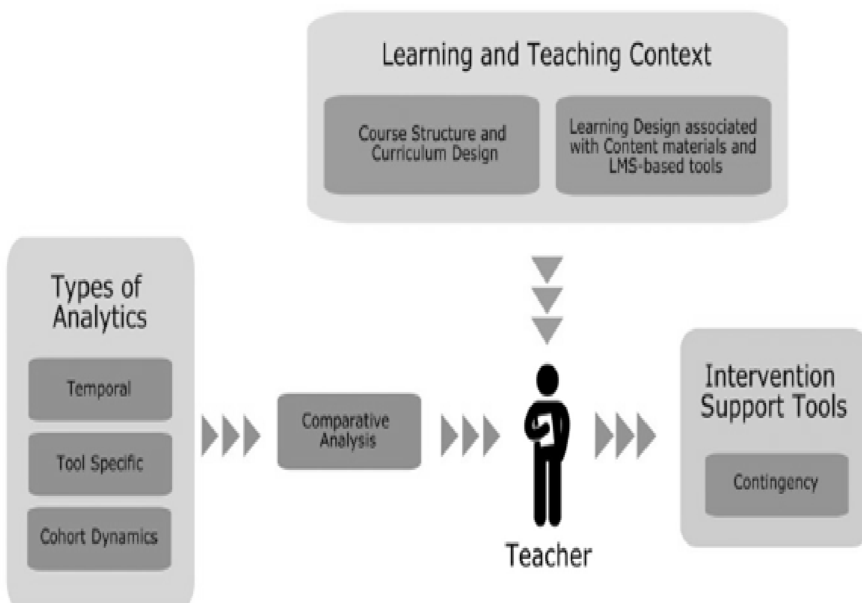


Figure 5. The learning analytics for learning design conceptual framework

Using this model, it is clear that LA design and pedagogy are highly intertwined. As such, it is critical to examine the role that pedagogical alignment plays in a faculty member's willingness to adopt LA.

Greller & Draschler (2012) conceptualize a LA framework around key dimensions: stakeholders, internal limitations, external constraints, instruments, objectives and data. Figure 6 depicts their framework. The framework emphasizes the complexity of LA and brings to light specific limitations and constraints. The research acknowledges the competencies of key stakeholders, as well as their willingness to accept the technology, influence usage and adoption. Furthermore, standard norms and conventions serve as external limitations of LA.

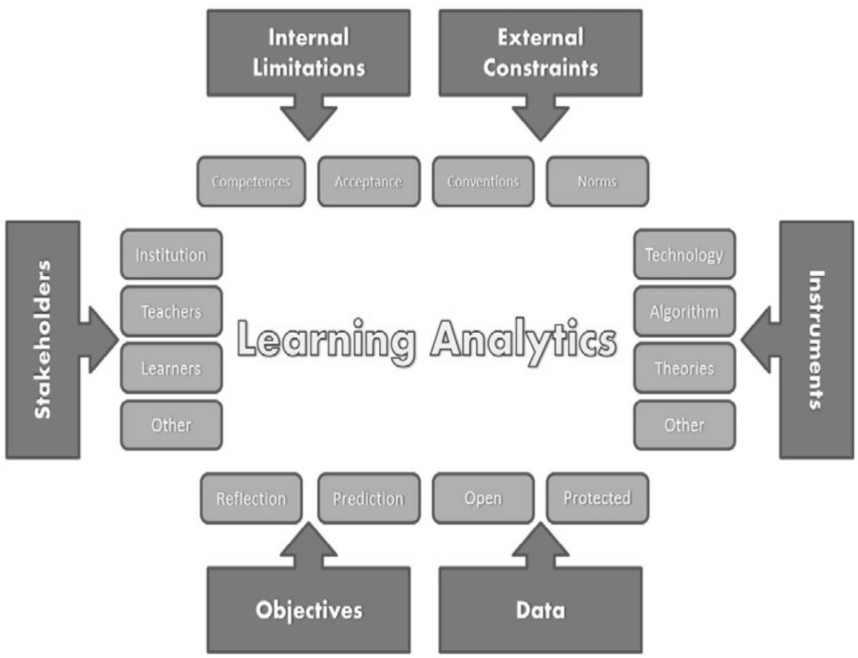


Figure 6. Critical dimensions of learning analytics

Echeverria, et al. (2018) stress the importance of data storytelling in LA through their conceptual model depicted in Figure 7. The model comes in response to an investigation on how faculty interpret data visualizations. The research shows that faculty have difficulty with sense making of LA. Faculty are able to construct basic stories based on the visualizations, but were unable to effectively determine if the story was accurate. Moreover, because faculty are unable to develop effective interpretations of the LA visualizations, little to no true insight can be garnered. The researchers argue analytic visualizations are more effective for faculty if the visualizations include data storytelling elements that help guide the end user in a particular direction. In essence, the story being told by the visualization should be self-evident to the faculty. Proper sense making can then lead to appropriate intervention strategies.

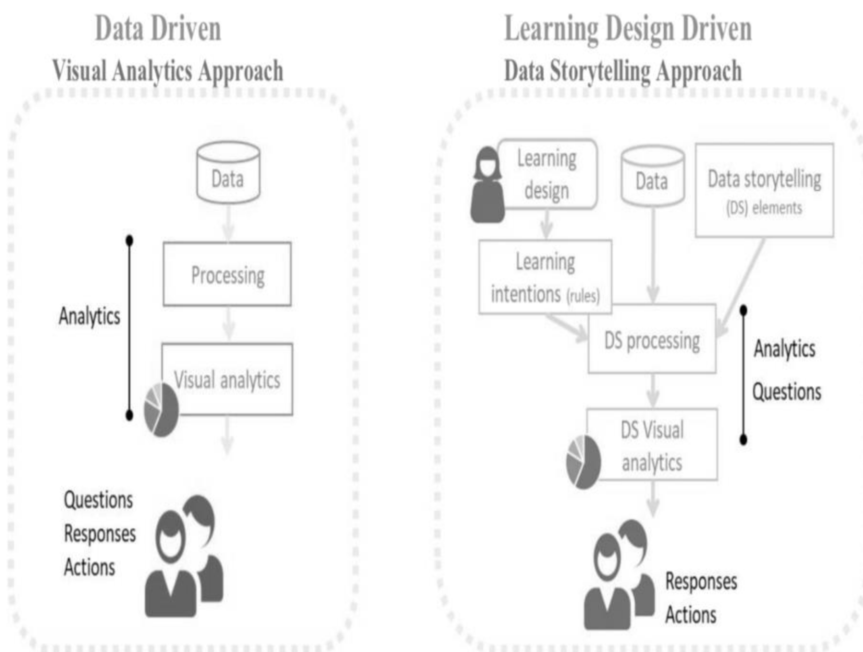


Figure 7. Data driven model vs data storytelling model of learning analytics design

The various definitions and conceptual frameworks illustrate that LA is a complex and evolving domain. Furthermore, higher education institutions that adopt a culture of analytics may find challenges with implementing a consistent set of integration objectives and policies. Given that faculty are at the heart of LA implementation and usage, research that seeks to understand the impact of LA efficacy on willingness to adopt is of value. A particular aspect of learning analytics systems is the exact design of the system; namely what data to display and how to display it. LA design represents a third key research stream found in the literature.

LA are typically presented to the end user in the form of a visual display. Often times the display takes the form of a dashboard. Basic elements of dashboards typically include colorful graphs, charts and standard quantitative data. There continues to be considerable work to understand the most effective visual display techniques (Echeverria, et al., 2018; Alhadad, 2018; Okan, Galesic, & Garcia-Retamero, 2016; Jorno & Gynther, 2018). Sense making of data is a challenge and Echeverria et al. (2018) address this directly by advocating that LA visualizations need to include storytelling elements in order to properly guide the stakeholder in the sense making process. An absence of such elements can lead to improper interpretations that subsequently lead to ineffective intervention strategies. Visualizations are a communication tool and proper consideration needs to be given to design (Alhadad, 2018). Specifically, Alhadad emphasizes seven guidelines for effective design that combine elements of visual attentiveness as well as cognition. Visual attentiveness is influenced by specific features of the element such as form, color and size. This is referred to as salience. A stakeholder's attentiveness and cognitive understanding can be influenced by their prior experience with similar visualizations. Chunking and visual clutter also contribute to effective design. The specific design elements of the LA visualizations are only part of the picture. It is the end user, the stakeholder, the data client, the student and the teacher that must interpret and act on the visualization. Okan, Galesic, & Garica-Retamero (2016) empirically test the influence of graph literacy on how individuals view health related graphs. The researchers measure eye tracking between a group of high graph literacy participants and a group of low graph literacy participants. Their findings show that participants with low graph literacy rely more on spatial-conceptual relationships such as tall bars means more, spend more time on textual features of graphs and ultimately have difficulty properly interpreting conflicts between the features of the visual elements and its true meaning. Conversely, participants with high graph literacy spend more time viewing the graph and elements that are specific and relevant to the cognitive task at hand. Perceived relevance of the LA display is critical. The perceived relevance is a part of the sense making process. It is through the sense making process that individuals reach a point of understanding and action. Good LA design will naturally lead to actionable insight (Jorno & Gynther, 2018). Actionable insights are garnered through review of the data and then subsequently acted upon. Jorno & Gynther (2018) suggest that LA design which focuses on actionable insight must give consideration to content, purpose, interpretation and outcome. These elements are critical because they vary tremendously from one learning analytic to another. Extrapolating from this research one can surmise that the needs of the faculty are not adequately being met through the current suite of LA systems. This provides further credence for the importance of faculty voice and ensuring the current state of LA by diverse faculty is clearly understood so that it can be leveraged in future design work and implementations. Diversity is an undercurrent of all the research in LA design. There is diversity in the design approach and diversity among the stakeholders. Researchers also vary on what types of data should ultimately be measured. Some argue that LA systems should be focused more on measuring "soft skills" which are the true needed skills for the future (Thompson D. , 2016). Others argue that LA algorithms that use traditional transactional data should not focus as much on prediction accuracy, but rather they should recognize the learning environment is much more diverse and as such LA algorithms should focus more on the transformative perspective (Kitto, Shum, & Gibson, 2018). Sense making will vary from individual to individual and designing for such diversity can be very challenging. If the result of the sense making process is ultimately confusion, the higher education faculty member may be less willing to adopt learning analytics. Given such complexity in LA design, goals and implementation strategies, it becomes clear that individual higher education faculty perceived efficacy of the learning analytics ecosystem could in fact play a key factor in willingness to adopt such technologies.

Looking forward, emerging themes in LA research include ethical data use and reporting as well data privacy (Campbell, Deblois, & Oblinger, 2007; Greller & Drachsler, 2012; Avella, Kebritchi, Nunn, & Kanai, 2016; Viberg, Hatakka, Balter, & Mavroudi, 2018). Ethics and privacy will continue to be critical areas of exploration and worthy of future study. Other identified gaps in the LA research include evidence based LA (Bollenback & Glassman, 2018; Gasevic, Dawson, & Siemens, 2015; Dawson, Gasevic, Siemens, & Joksimovic, 2014; Ferguson, et al., 2016; Mahroeian, Daniel, & Butson, 2017), LA research based in theory (Greller & Drachsler, 2012; Echeverria, et al., 2018) and increased stakeholder involvement (Ferguson, et al., 2016; Viberg, Hatakka, Balter, & Mavroudi, 2018; Herodotou, et al., 2017; Mahroeian, Daniel, & Butson, 2017).

Extent Technology Adoption Models & Learning Analytics Adoption

Extent technology adoption models are an important foundation for any current technology adoption research. LA represents a new technology. And the complexity of the systems, tools and stakeholders for learning analytics provides a unique arena to explore technology adoption. Perhaps one of the most influential technology adoption models was developed by Davis when he explored the role of perceived usefulness and perceived ease of use in his technology adoption model; TAM (Davis F. , 1989). As of the time of this writing, Davis’s work has been cited over 74400 times according to Google Scholar. Davis believed that the more a technology was perceived as useful to the end user, and the more the technology was perceived as easy to use by the end user, the more apt that end user is to adopt that technology. In the ensuing years, Venkatesh and Davis extend TAM into TAM2 by examining the role of social influence on technology adoption and performing a more in-depth investigation into determinants of perceived usefulness (Venkatesh & Davis, 2000). As it specifically pertains to their work in perceived usefulness, they investigate the role of job relevance and output quality. These are important foundational ideas in which to bridge to LA adoption. It becomes apparent that LA adoption will be influenced by the degree to which a higher education faculty member views LA as relevant to their job and how they view learning analytics align to their occupational goals. TAM was extended a second time to TAM3 with the work of Venkatesh and Bala (Venkatesh & Bala, 2008). The model proposed in TAM3 is comparatively more complex than its predecessors. The model seeks to explain how the end user's past experience interacts with the role that computer anxiety plays on perceived ease of use and the interaction of perceived ease of use with perceived usefulness and behavioral intention. The interaction of experience to other constructs within the research model proposed in this work was deemed out of scope for the current study. However, the role of experience is still an important consideration within this study as experience and was examined as a control variable in the theoretical model. It is important to observe that in the time between TAM2 and TAM3, a research model was proposed that sought to unify many of the prior technology adoption models (Venkatesh, Morris, Davis, & Davis, 2003). The unified theory of adoption and use of technology model, UTAUT, draws on prior research with TAM and additionally with prior work in job-fit. The role that job-fit plays in technology adoption has been examined by Thompson and others (Thompson, Higgins, & Howell, 1991; Goodhue & Thompson, 1995). Job-fit speaks to the degree to which a given technology fits with a certain job. Within the UTAUT model, job-fit manifests itself within the performance expectancy construct. Additionally, the UTAUT model includes effort expectancy. The fundamentals of effort expectancy trace back to the ease of use ideas of Davis (Davis F. , 1989). As it pertains to the current project on LA adoption, effort expectancy and performance expectancy play key roles in the theoretical model. It is important to examine how foundational technology models perform over time as the individual technologies change. LA represents a relatively new technology. As such, examining how certain aspects of TAM or UTAUT apply to LA adoption becomes a worthy pursuit. The effort provides further support for influential adoption models and helps to solidify their presence and importance.

End user's perception of the technology to be adopted is a critical element for understanding the full landscape on what drives technology adoption (Moore & Benbasat, 1991). Moore & Benbasat (1991) acknowledge information system and adoption theories have been criticized as lacking a strong theory base and that instruments to measure proposed theory have lacked psychometric rigor. The researchers grounded their work in the existing diffusion of technology research (Rogers, 1983), in which five influential technological adoptions were identified; namely relative advantage, compatibility, complexity, observability and trialability. Working from this foundation, Moore & Benbasat theorized the following constructs in their model; voluntariness, relative advantage, compatibility, image, ease of use, result demonstrability, visibility and trialability. It is important to highlight this particular project as it influenced later work with UTAUT (Venkatesh, Morris, Davis, & Davis, 2003) and UTAUT is a critical element of the theoretical model proposed to identify critical factors that influence LA adoption. Items from the Moore & Benbasat work were included in the original pilot survey of this work, but were later adjusted to more closely align with the performance and effort expectancy items used to measure UTAUT.

The cultural environment for LA adoption may not be fully matured. In their review of adjunct faculty perceptions of LA, Boolenback & Glassman (2018) find that while most faculty had strong computer literacy and believed that LA added value to the feedback process, relatively few actually adopt LA into their professional practice. Faculty buy-in was deemed essential as evidenced by the following (2018, p. 77), *"In an era where student learning must be measured and more frequently aligned with industry needs, a sound learning analytics strategy is a must as well as buy-in from the faculty who make up the future end-users of such a platform."*. Large scale adoption of LA continues to be an issue and is heavily influenced by the organization's leadership and culture (Dawson, et al., 2018). Identified LA adoption barriers include perceived lack of effectiveness, lack of required skills to use the analytics, current workload and lack of organizational support to name but a few (Herodotou, et al., 2017). Others point towards adoption challenges as it relates to LA exhibiting a poor human centered design (Dollinger, Liu, Arthars, & Lodge, 2019; Rehrey, Shepard, Hostetter, Reynolds, & Groth, 2019; Quintero & Selwyn, 2018). Stakeholder buy-in as well as evidence based implementation support are deemed as critical factors that could impede or promote LA adoption (Ferguson, et al., 2016; Norris, Baer, Leonard, Pugliese, & Lefrere, 2008). Recent research has shown that LA adoption continues to be sporadic at best and when implemented, typically the adoption is on a relatively small scale (Alzahrani, et al., 2023). The aforementioned research finds the following challenges that HEI have when implementing LA at scale; ethical issues, cultural change resistance, issues with analytics capability models, and the influence of stakeholder buy-in. Stakeholder buy-in is an essential element to highlight as it strikes at the heart of the current research. Two additional research projects into the adoption and usage of LA dashboards show that stakeholders believe there to be value in LA tools, but still struggle to consistently and effective adopt LA into day to day professional practice (Kaliisa, Gillespie, Herodotou, Kluge, & Rienties, 2021; Rienties, Herodotou, Olney, Schencks, & Boroowa, 2018).

As is evidenced in the literature, LA adoption is not common place in higher education institutions and the factors that influence adoption are layered. Some of those layers are grounded in foundational technology adoption models. While other layers are continuing to emerge.

Organizational Culture of Learning Analytics and Readiness Factors

There exists great pressure to make informed and impactful decisions based on data; both at the personal and business level. As businesses race to integrate data and data driven decision methodologies into their organizations, the need to understand the role of an analytics culture arises. Success of the institution may hinge on their ability to adopt a data driven model for critical strategic and operational initiatives. Organizational culture plays a large role in quality management and performance (Naor, Goldstein, Linderman, & Schroeder, 2008). Investigations into organizational culture within HEIs are at a subordinate level to standard commercial businesses. Organizations that culturally have an over reliance on decision support systems may indeed fail to meet their objectives (Aversa & Cabantous, 2018). It is important to understand the key factors that minimize failures when utilizing decision support systems (DSS) or data driven decision-making methodologies. A blind adoption of a DSS that is void of critical review may culminate in unintended and undesirable outcomes. Data and analytics should ultimately empower the knowledge worker and make them more effective in their role. A culture of analytics should clarify and not cloud. Moreover, LA adoption on a large scale in higher education is sporadic at best (Dawson, et al., 2018; Alzahrani, et al., 2023). Researchers seem to concur that more work is needed to explore and mitigate barriers to LA adoption (Herodotou, et al., 2017; Viberg, Hatakka, Balter, & Mavroudi, 2018; Ferguson, et al., 2016; Gasevic, Dawson, & Siemens, 2015). Research points to LA design, training, staff support and lack of time as key adoption challenges (King, 2017; Herodotou, et al., 2017); which are important, but all matters of logistics.

There is broad based consensus that LA have a pervasive goal in aiding the decision making process of stakeholders that persistently takes place in various learning contexts (Bakharia, et al., 2016; Greller & Drachsler, 2012; Avella, Kebritchi, Nunn, & Kanai, 2016; Alhadad, 2018). The value proposition of LA systems is clear (Avella, Kebritchi, Nunn, & Kanai, 2016) *"Going forward, schools must recognize the importance of implementing a data-driven approach to education. The use of performance systems allows for increased and more productive decision-making, the identification of trends and problematic areas, and the more efficient allocation of resources."* (p. 25). History shows that more and more universities are embracing LA into their organizational culture, but at a generally slow rate. This emerging phenomenon is worthy of additional study.

An organizational culture that reflects a high value of the usage of data and analytical tools to enrich and deepen the educational experiences of faculty and students will likely be an enabler to an individual higher education faculty member's willingness to adopt LA.

Institutional readiness factors refer to the how well the organization is equipped to implement a particular initiative. This positioning can be based on financial capacity, intellectual capacity, or technical capacity. It is important that an organization with a certain culture also has the true capacity to carry out that culture. Specifically with LA adoption, if the institution does not currently have the technical systems in place to capture insightful educational data and they do not carry the financial ability to acquire such systems, it is unlikely that an individual higher education faculty member will choose to adoption LA; even on a small scale. Early work in building capacity for LA readiness points to clearly delineating various goals of the analytics as well as creating an infrastructure that evaluates the analytics to inform future decision making (Norris, Baer, Leonard, Pugliese, & Lefrere, 2008). Later work theorizes the DELTA model can be used to classify data driven maturity levels within an organization (Lismont, Vanthienen, Baesens, & Lemahieu, 2017). DELTA is an acronym that represents Data (high quality), Enterprise orientation, Leadership (in analytics), Targets (strategic), and Analysts. Each of these in turn plays a key role in creating a comprehensive culture that fully embraces data driven decision making behaviors. Or more specifically, institutional readiness factors that well position an institute of higher education to embrace and implement LA. The DELTA model was used to classify four different levels of data analytics integration within various companies; no analytics, analytics bootstrappers, sustainable analytics adopters, and disruptive analytics innovators. Two important takeaways emerge from the research on DELTA. First, while analytics teams are growing, the required skills to implement and find value from analytics requires a very diverse set of skills. Second, data analytics integration is still forming within organizations and as such there is a wide variety of maturity models with most organizations falling into the bootstrapper level. Analytics bootstrapper organizations have a limited number of years of experience using analytics and while they believe in the value of data driven decision making, most still rely on intuition. Determining where higher education institutes rank in the four data maturity models is out of scope for this current project. However, it is likely that most higher education institutes fall in the bootstrapper category as it applies to integration of learning analytics. There may exist a strong belief in the power of LA, but adoption and integration is slow and the maturity of the analytics culture is still emerging.

An alternate way to view LA readiness factors is through the lens of business intelligence readiness factors. Business intelligence is perhaps an older term than data driven decision making, but they are in essence the same. At the core, data and information are being used to drive purposeful business decisions. A thorough review papers on business intelligence readiness factors points to three major themes; organizational, technological, and social (Hasan, Miskon, Ahmad, Syed, & Maarof, 2016). The project examined sixty different papers on business intelligence readiness factors to extract the major themes. The importance of readiness factors comes to light as the research teams specifically highlight (2016), *"Moreover, the state of the 'readiness' among participants is important as to ensure the new system implementations are able to be accepted."* (p. 179). When exploring end user adoption of technology, it is important to consider the role that perceived institutional readiness plays. The current research does not seek to extract specific quantitative measures of readiness. For example, the number of databases available to faculty was not counted. Or the number of specific professional development activities to advance learning analytics usage was not counted. However, it is apparent that institutional readiness for LA and how the key stakeholder of the faculty member perceives that readiness are important considerations for understanding the LA adoption puzzle.

Professional Identity

As previously mentioned, the first annual international conference on Learning Analytics in 2011 presents an important definition for learning analytics (Siemens, Long, Gasevic, & Conole, 2010): *"The measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and environments in which it occurs."* (p. 1). Inherent in this definition is the notion of optimization. Optimizing learning translates to making the learning process as efficient as possible with the highest possible quality standards. This conceptualization of learning analytics utilizes economic values and principles. This viewpoint of learning analytics is further supported by Quintero & Selwyn (2018) where they specifically critique the digitization of higher education as being *"consumed along economically rational lines."* (p. 32). Radu (2017) also argues the goal of optimizing student learning when describing learning analytics as an act involving collecting and measuring learner data. These definitions are essential when considering the influence of professional identity expectancy on willingness to adopt. Key constructs like optimization and economic rationality may, or may not, align with how an individual faculty member views their professional self. As such, there may, or may not, be an alignment between LA and a self-actualized professional identity. This alignment may be a key influencer in willingness to adopt.

At the heart of the faculty member's work experience is their professional identity. Research points to professional identity key constructs as belonging, attachment, beliefs and institutional logics (Barbour & Lammers, 2015). The professional identities for some teachers shows variability over time and may be influenced by the institutional environment in which they work (Day, Kington, Stobart, & Sammons, 2006). The purpose of this research project is not intended to further examine the key constructs that make up one's professional identity. Nor is the focus to examine the stochastic stability of a higher education faculty member's professional identity. The purpose of this research is to examine how the strength of the alignment between the goals of LA and the faculty member's professional identity impacts the faculty member's willingness to adopt LA. Fundamental questions pertaining to perceptions of alignment to professional identity are not sufficiently addressed in the LA literature. Professional identity is a key driver for how a higher education faculty member carries out their professional tasks and interacts with other actors in their professional system (Trede, Macklin, & Bridges, 2012). In essence, professional identity informs and shapes attitudes and behavioral actions. The manner in which an individual perceives their professional identity influences the actions they take as a professional. For example, a higher education faculty member that defines part of their professional identity as being responsible for growing the body of knowledge within their area of expertise is much more likely to engage in formal scientific research. Or if a faculty member includes characteristics of altruism in their professional identity, they are much more likely to be available to students who need additional support. Professional identity is an important component for understanding what drives professional behaviors. As such, it is important to understand how individual knowledge workers (higher education faculty) reconcile the emergent culture of analytics within higher education institutions with their professional identity as educators. Educators often take on the persona of teaching being more of who you are and not so much of what you do (Korthgen, 2004). Here again we see how the role of professional identity will influence behaviors. For example, assume a faculty member believes that at the core of being a teacher is the relentless commitment to improving the student learning experience. Furthermore, assume the same faculty member views a goal of LA to uncover and bring to light pedagogical issues that contribute to impaired student learning. Therefore, the LA are seen as a tool that can be used to improve the learning experience. In this case, there is strong alignment between the disparate views on professional identity and learning analytics. Stated differently, if a higher education faculty member has an expectancy that LA align with their own professional identity, that faculty member may be more willing to adopt LA into their professional practice. This strong alignment is hypothesized to be an enabler of willingness to adopt learning analytics. Conversely, a misalignment is hypothesized to be a threat of willingness to adopt.

Theory Base - TPACK

The origins of the Technology-Pedagogy-Content-Knowledge framework are traced to the work of Shulman on the interaction between pedagogy and content knowledge (PCK) that fuels successful educators (Shulan, 1986; Shulman, 1987). Shulman brings to light that in the 1800's teacher credentialing was based largely on content knowledge such as knowledge of mathematics and grammar. However, at that time, little emphasis was placed on pedagogical knowledge. A shift then occurred with teacher education and credentialing whereby the art of teaching and the pedagogical knowledge was more important than content knowledge. His argument is the two domains are both essential. Successful educators need content knowledge in their own domain of expertise. But they also require excellent pedagogical knowledge to effectively communicate that content knowledge. This sentiment is fully captured in his words, *"But the key to distinguishing the knowledge base of teaching lies at the intersection of content and pedagogy, in the capacity of a teacher to transform the content knowledge he or she possesses into forms that are pedagogically powerful and yet adaptive to the variations in ability and background presented by the students."* (Shulman, 1987, p. 15). The core content-pedagogy knowledge model was extended by Mishra & Koehler to include technology knowledge (Mishra & Koehler, 2006). This is an important extension because educational technology represents a highly influential phenomenon in field of teaching. Education technology can serve as a disruptor. As such, extending the model of critical knowledge domains past content and pedagogy into technology is critical. The technology-pedagogy-content knowledge (TPCK) recognizes not only the importance of each individual knowledge area, but also the interplay that occurs between the areas. For example, pedagogical knowledge focuses on the teacher's knowledge on the processes and practices involved in effective education. Technology knowledge, which is typically in a high rate of change based on the speed of technical innovations, focuses on the teacher's knowledge of specific technologies like a personal computer, simulation software, or LA. The interaction of pedagogical knowledge and technical knowledge captures how the individual teacher is able to apply the right technologies to aid in the delivery of certain pedagogical practices. This combination of knowledge can be captured in the understanding of how to use LA in order to adapt ineffective teaching strategies into a more successful strategy. TPCK evolved to TPACK in 2009 when Koehler & Mishra presented a more condensed and updated version of their theoretical model on knowledge domains for teachers (Koehler & Mishra, 2009). The work continues in 2013 when a final model is presented; see Figure 1 (Koehler, Mishra, & Cain, 2013). As the work in TPACK has continued through the years, a considerable effort has been put forth to strengthen the theoretical base of TPACK and also to develop effective instruments to measure TPACK. For the purposes of the current research, TPACK provides an essential theoretical lens. The technology knowledge construct from TPACK is operationalized through LA tools and technology efficacy and data cycle literacy. The pedagogical knowledge construct is operationalized in the current research through effort expectancy and performance expectancy. The content knowledge is operationalized through professional identity expectancy. Lastly, the interaction of all three knowledge areas; technology-pedagogical-content, takes shape in willingness to adopt learning analytics into professional practice.

Conclusion

The aforementioned literature in Chapter 2 highlights the complexity of issues in fully understanding what exactly are LA and what are the required skills to effective utilize LA. Chapter 2 described the current literature base used as a foundation for exploring the current organization culture of learning analytics usage and adoption, technology adoption theory, underpinnings of professional identity, and TPACK as the theoretical base for the research project. A review of the literature shows a gap as it pertains to the influence that professional identity has on willingness to adopt LA into professional practice. Additionally, the literature supports the value of the effort to validate existing technology adoption theories against new technologies such as LA

Chapter 3. Research Methodology

The goal of this study was to explore critical factors that influence a higher education faculty member's willingness to adopt LA into their professional practice. The fundamental theorized factors included LA efficacy as realized through LA tools and technology efficacy and data cycle literacy, performance and effort expectancy, professional identity expectancy, and institutional readiness. The value of this study was realized through the congruence with existing literature in the field of learning analytics as well as filling a gap as it specifically pertains to extending traditional technology adoption theories to LA and exploring the role that professional identity plays in willingness to adopt. This chapter presents a research methodology agenda that is consistent with previous studies in technology adoption.

Part 1: Research Design & Survey Instrument Development

The research agenda described is exploratory behavioral research with an emphasis on theory testing. The substantive quantitative analysis is the emergent culture of LA adoption as examined through the lens of the higher education faculty member. The underlying high level research question for this agenda was the following: What influences a higher education faculty member's decision to adopt, or not adopt, learning analytics into their professional practice? This high level question led to the following specific research questions:

RQ1: What are the emergent enablers to a higher education faculty member's willingness to adopt learning analytics into their professional practice?

RQ2: What role does the concept of professional identity expectancy fill in determining a higher education faculty member's willingness to adopt learning analytics?

This study leveraged the definition of learning analytics provided at the international conference on Learning Analytics in 2011 (Siemens, Long, Gasevic, & Conole, 2010): *"The measurement,* *collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and environments in which it occurs."* (p. 1). Using this definition as the benchmark for LA, it was important to learn the correlational relationships between the aforementioned constructs and a faculty member's willingness to adopt and implement LA into their professional practice. Surveys provide a valuable tool for the collection of data used to determine the strength of correlational relationships; especially when performing quantitative research aimed at testing a theoretical model. Quantitative data can be collected via surveys and then used in statistical analysis. Under this premise, a pilot study was created and analyzed to ascertain potential independent constructs as well as to inform an effective final survey design. Constructs were measured using items informed by research and were constructed using Likert scales for responses. A thorough review and analysis of the pilot study led to the creation and distribution of the final survey. Results from the final survey were analyzed using SAS JMP Statistical Discovery Pro 15.0. These results guided final conclusions and insights.

Determination of Research Subjects

The main subject of study is the higher education faculty member. As compared to elementary and secondary schools, learning analytics are emerging on a greater scale within higher education institutions. The Signals program at Purdue University is one such example (Arnold & Pistilli, 2012). For the purposes of this study, higher education institutes include any institution within the United States that award a two year associates or master's degree, a four year bachelor's degree, or any doctoral degree. To be eligible for the study, the survey respondent must be a full time faculty member at such an institution. This research focused on the adoption of LA as seen through the lens of the higher education faculty member. A pilot study was constructed in Survey Monkey and the link to complete the survey was distributed via email to faculty at a small university located in the Midwest region of the United States. A representative at the university emailed the link via a generic faculty distribution list. As such, the principle researcher of this project was not directly involved in determining survey respondents. Additionally, by using a generic faculty distribution list, individual faculty members were not explicitly targeted. The final survey was also built in Survey Monkey. Distribution of the final survey was completed using the distribution support services as provided by Survey Monkey. The Survey Monkey distribution mechanism can target individuals that work in the education sector, but it cannot specifically target higher education faculty. As such, a filter question was added at the beginning of the final survey. The filter question asked the respondent what their primary role was in the education industry. If a respondent selected, “Full time higher education faculty at an institution that awards 2 year, 4 year and/or doctoral degrees”, they were presented with an opportunity to complete the full survey. Otherwise, the respondent was not allowed to complete the survey and the survey process was terminated. All responses were collected regardless of whether or not the respondent completed the entire survey. Subsequent review of the collected data from the final survey yielded 222 fully completed surveys that were used for final analysis.

Initial Pilot Survey

A pilot survey was conducted in order to test the initial research model. The items in the original pilot survey were informed through research, but eventual analysis of the results showed modifications were required to build a stronger final survey. Additionally, the number of respondents for the pilot survey was very low; n = 16. The initial pilot survey was built in Survey

Monkey and the link to the survey was distributed to faculty at a small Midwestern university using a generic faculty email distribution list. Items in the original pilot study were presented individually using their own respective Likert scale. This design added complexity and likely increased the cognitive load required to complete the survey. This design was modified in the final survey whereby items were congregated based on the construct being measured and were presented via a matrix style with individual items listed in the left most column, a single Likert scale presented on the first row, and radio buttons to select in the inner grid.

The items in the pilot study were mainly informed through previous work in technology adoption (Dunn, Airola, Lo, & Garrison, 2013; Goodhue & Thompson, 1995; Hasan, Miskon, Ahmad, Syed, & Maarof, 2016) but in some instances, especially with regards to professional identity, new items were created. Within the initial pilot survey, a single item was used to measure current usage and a single item was used to measure the dependent construct of intention to use. Additionally, LA efficacy was measured through three constructs; data tools and technology efficacy (six items), data visualization efficacy (four items) and data cycle literacy (four items). The original items in the pilot survey were informed by research into teacher efficacy and concerns as they pertained to data driven decision making (Dunn, Airola, Lo, & Garrison, 2013). Pedagogical alignment was measured through two constructs; task fit and performance expectancy. Task fit (twelve items) measurement was informed by a previous survey instrument used to measure the role that task fit plays in technology adoption (Goodhue & Thompson, 1995). Performance expectancy (twelve items) was measured using work of Venkatesh et al. with creating a unified model for user acceptance of technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003). The UTAUT project leveraged multiple prior studies in technology adoption and worked to create a composite survey instrument based on items used within those prior studies. As such, the researchers worked to create a single unified view and model to explain factors influencing user adoption of technology. An existing measurement instrument for professional identity was not found and as such, new items were created for the survey. However, the items were highly influenced by the work on Barbour & Lammers (2015) who explored measuring professional identity within the healthcare professionals by way of a confirmatory factor analysis strategy. The researchers of this model focused on constructs of professional commitment, belief in autonomy, belief in self-regulation, belief in economics of managed care, belief in managed care organizations and experienced autonomy. The final independent construct, which was also theorized to have an interaction effect with LA efficacy and pedagogical alignment was LA readiness. LA readiness (four items) items was informed by research conducted into organizational preparedness for LA (Baer & Norris, 2017). Lastly, three control variables were measured; level of teaching experience, technology adoption category which were leveraged from prior research (Moore & Benbasat, 1991; Rogers, 1983), and teaching discipline. While items were informed through literature, there was not a consistent number of items used across the constructs. Some high level constructs were measured using as many as fourteen items and others used only four. This inconsistency was challenging to work with. Data analysis showed poor loading consistency amongst certain constructs and poor correlations to the dependent construct. A return to the literature used unveiled inconsistencies with items selected from previous survey instruments. These inconsistencies were addressed, and in places, different survey instruments were used to inform the final survey. The pilot study used a single item to measure the dependent construct. After analyzing the results and consulting with more experienced researchers, four items were created and used in the final survey. Through additional discussions and meetings with more experienced researchers, the three control variables in the initial theoretical model were expanded to five.

The pilot survey was distributed to faculty at a small university in the Midwest region of the United States. Unfortunately the number of respondents was small, n=16. While the number of respondents were small (n = 16), there were usable insights gained that informed the revision of the survey and research model. There were structural issues with the pilot survey with regards to overall design and language. Many of the items within the pedagogical alignment construct showed low or contradictory correlations. Data visualization efficacy showed virtually no correlation to the dependent construct. As such, after thorough review and additional professional consultation, the survey was revised into its final form.

Final Survey Instrument and Questions

While the initial pilot survey did present challenges that mostly occurred because of inexperience of the researcher, the results and process were extremely valuable and informative. The experience shaped the creation of the final survey. The final survey corrected design issues with cognitive load for the respondent, inconsistencies with number of items being used to measure constructs and the strategic choices of previous research work that would be used to inform the wording for the final items. The final form was simplified and improved structurally to reduce the cognitive load and time required to complete. New items were added that were better supported via the literature. Additional control variables were also added.

The final survey aligns to the final research model. LA efficacy is envisioned through two independent constructs; LA tools and technology efficacy (eight items using a five point Likert scale) and data cycle literacy (four items using a five point Likert scale). The items used to measure LA efficacy were author created but influenced by prior research (Dunn, Airola, Lo, & Garrison, 2013). In the pilot survey, pedagogical alignment was comprised of the independent constructs of task-fit and performance expectancy. The final model replaced task-fit with effort expectancy and as such the final survey included items for effort expectancy (four items using a five point Likert scale) and performance expectancy (six items using a five point Likert scale).

The instrument used in testing the Unified Theory of Acceptance and Use of Technology (UTAUT) provides a strong foundation for this research (Venkatesh, Morris, Davis, & Davis, 2003). The initial survey used in UTAUT included fourteen items to measure effort expectancy and twenty four items to measure performance expectancy. Not all items were used in the final UTAUT model. Based on data analysis and simplicity of the original UTAUT model, four of the original fourteen and four of the original twenty four were used to measure effort expectancy and performance expectancy. The four final items used for effort expectancy in the UTAUT study were adapted with slight wording changes for the current study. A review of the original twenty four items to measure performance expectancy within UTAUT revealed six that were appropriate for this study. Two of the final items used to measure performance expectancy in UTAUT were used in this study and were slightly adapted for appropriate wording changes. Four additional items were taken from the original list of items used in UTAUT.

Professional identity expectancy (four items using a five point Likert scale) is the third independent construct. The items were author created, but influenced from prior research (Barbour & Lammers, 2015).

The interaction effect as influenced by perceived institutional learning analytics readiness was measured with five items each using a five point Likert scale. Organizational culture and infrastructural readiness are important elements of successful business intelligence project implementation success (Hasan, Miskon, Ahmad, Syed, & Maarof, 2016; Norris, Baer, Leonard, Pugliese, & Lefrere, 2008). The principal focus of study for the current learning analytics adoption study is the higher education faculty member. It is through their lens that willingness to adopt is being investigated. Congruent to that line of thinking, institutional readiness is measured through the faculty member's perception of the institution's readiness. It is understood that perceptions will widely vary, even within the same institution. Future work could include data collection that more objectively measures an institution's data centric culture.

The dependent construct measuring the behavioral intention of willingness to adopt was modified from its original version in the pilot survey of a single item to include four distinct items that sought to uncover differences between hope and intention as well as temporal differences between short and long term willingness to adopt. The number of control variables were also increased in order to validate a more robust model. Table 1 summarizes the final survey instrument and measurement items.

Table 1. Construct measurements

Construct	Measurement Items	Likert Scale	Source
Learning Analytics Tools and Technology Efficacy	• Identifying the appropriate learning analytics needed to assess <u>individual student</u> performance. • Identifying the appropriate learning analytics needed to assess <u>group level</u> performance. • Using learning analytics tools to retrieve charts, tables or graphs for analysis. • Using learning analytics tools to filter students into different groups for analysis. • Using learning analytics tools to access student performance reports. • Describing learning analytics information presented in column charts, bar chart or pie charts. • Describing learning analytics information presented in radar charts, heat maps or social network graphs. • Determining actionable insight from learning analytics.	Not At All Confident Slightly Confident Somewhat Confident Fairly Confident Completely Confident	Author created Influenced by Dunn, Airola, Lo, & Garrison, 2013.

Construct	Measurement Items	Likert Scale	Source
Data Cycle Literacy	• Explaining the data cycle model. • Describing how the data cycle model provides a foundation for learning analytics technologies. • Correlating different phases of the data cycle model to your usage of learning analytics. • Explaining how the data cycle process flow is reflected in the art of teaching.	Not At All Confident Slightly Confident Somewhat Confident Fairly Confident Completely Confident	Author created
Effort Expectancy	• My interaction with learning analytics would be clear and understandable. • It would be easy for me to become skillful at using learning analytics. • I would find learning analytics easy to use. • Understanding how to use learning analytics is easy for me.	Strongly Disagree Disagree Equally Disagree / Agree Agree Strongly Agree	Venkatesh, Morris, Davis, & Davis, 2003
Performance Expectancy	• Enable you to accomplish your pedagogical tasks more quickly. • Improve your pedagogical performance. • Increase your productivity. • Enhance your pedagogical effectiveness. • Make it easier to do your job. • Increase the quality of output in your job.	Strongly Disagree Disagree Equally Disagree / Agree Agree Strongly Agree	Venkatesh, Morris, Davis, & Davis, 2003
Professional Identity Expectancy	• Incorporating learning analytics into my teaching practice would make me feel closer to the professional community of higher education faculty members. • I could better achieve my professional goals by using learning analytics in my practice. • Using learning analytics would help me to better realize my vision of what it means to be a higher education faculty member. • I believe the purpose of learning analytics reflect my version of the core ideals of being a higher education faculty member.	Strongly Disagree Disagree Equally Disagree / Agree Agree Strongly Agree	Author created Influenced by Barbour & Lammers, 2015.
Perceived Institutional Learning Analytics Readiness	• Possesses the technical infrastructure (databases, networks, applications, etc.) required to implement learning analytics technology. • Has executive sponsorship that promotes data informed decision making. • Recognizes individuals that incorporate data into various decision making processes. • Provides enough training for me to find and access learning analytics. • Offers professional development opportunities to advance my knowledge and skills required to use learning analytics.	Strongly Disagree Disagree Equally Disagree / Agree Agree Strongly Agree	Norris, Baer, Leonard, Pugliese, & Lefrere, 2008 Baer & Norris, 2017
Willingness to Adopt Learning Analytics	• I hope to use learning analytics in the coming academic year. • I intend to use learning analytics in the coming academic year. • I hope to use learning analytics in the next 2-5 years. • I intend to use learning analytics in the next 2-5 years.	Strongly Disagree Disagree Agree Strongly Agree	Author created

Construct	Measurement Items	Likert Scale	Source
Control Variables	• Do you currently use learning analytics in your professional practice? • Do you tend to use traditional external review information, such as student feedback surveys, to improve your professional practice? • How do you self-identify your technology adoption behavior? • How many years have you been teaching in higher education? • What is your primary teaching discipline? • What is the approximate percentage of in-person, online or hybrid classes that you teach?	Response options vary by question	Author created Technology adoption behavior taken from Moore & Benbasat, 1991 & Rogers, 1983.

Part 2: General Data Collection and Analysis Methodologies

Survey Respondents

Purposeful action was taken with the final survey to ensure a sufficient number of responses were returned. The final survey was developed using Survey Monkey. Survey Monkey was also leveraged for survey distribution support. A filter question was added to the final survey to ensure that only faculty at degree awarding higher education institutions were allowed to complete the survey. Survey responses were initially collected through Survey Monkey in the summer of 2022. The responses were subsequently downloaded and initially cleansed in Microsoft Excel. 1330 initial responses were collected. However, most were removed because the respondent was not a higher education faculty member. In the end, of 1330 initial survey respondents, 259 indicated they were higher education faculty. From the 259 higher education faculty responses, 37 were removed because the survey responses were incomplete. For these 37, some questions were answered and some were not. Any survey that was not fully completed was removed from analysis. This resulted in a final number of 222 survey responses used for full analysis. This number is significantly improved from the low number of pilot study responses. Minor data cleansing and reformatted was conducted in Microsoft Excel 2016. Items were provided a unique identifier and where required, numerical responses were converted to their corresponding nominal variable data. For example, Survey Monkey recorded the numerical values of 1-7 for specific teaching disciplines. The numerical values were converted to the text value. A specific example is the numerical value of 1 was converted to "Business (Accounting, Finance, Business Management, etc.)". After initial data cleansing and preparation was completed, the response data was imported to SAS JMP Statistical Discovery Pro 15.0.

Item Analysis

Each of the items from the survey were evaluated to determine near-normal distributions. Traditional boxplots and descriptive statistics were used to evaluate individual item variance. No item demonstrated poor variance. Intra-item correlations and exploratory factor analysis were used to ensure relatively high correlations within predefined constructs. Finally, confirmatory factor analysis was used to ensure that items are properly loading on factors consistent with the research model. As the independent constructs are assumed to be mutually independent, a Varimax rotation methodology was used within the factor analysis process. Most all items properly loaded on factors that were consistent with the research model. It should be noted that effort expectancy, performance expectancy, and professional identity expectancy did load highly on a single factor. This gives credence to the notion that these respective constructs, while different, demonstrate communal relationships. However, there is enough evidence to support the construct reliability and validity needed to perform in-depth statistical analysis required to confirm or discount the proposed hypotheses.

Analysis of Data and Hypothesis Confirmation

Structural equation modeling (SEM) techniques allow the researcher to concurrently examine a multitude of dependency relationships proposed in a theoretical model (Hair, Black, Babin, & Anderson, 2015). SEM is very effective in describing the structure and strength of the relationships that exist between latent factors and constructs. Moreover, it is an effective process to describe a collection of relationships. SEM can be looked at as a tool to determine the "fit strength" of a theoretical model; often referred to as goodness of fit metrics. Multiple statistical measures help to describe the goodness of fit of SEM models. As it relates to sample size, a minimum sample size of 150 is suggested when the model has seven or fewer constructs, modest communalities (0.5), and construct completeness in so much as no construct was under-identified (Hair, Black, Babin, & Anderson, 2015). The sample size of 222 exceeds this minimum advised threshold. Within SEM, traditional independent variables are described as exogenous and dependent variables are described as endogenous. Within the proposed theoretical model, exogenous variables include learning analytics tools and technology efficacy, data cycle literacy, effort expectancy, performance expectancy, professional identity expectancy, and perceived learning analytics readiness as it pertains to an interaction effect with effort expectancy and performance expectancy. The single endogenous variable is willingness to adopt learning analytics. Within the SEM process, first a measurement model is created and analyzed. The measurement model often assumes no dependence relationship and simple assumes that all constructs in the theoretical model are exogenous. Under this guise, the measurement model examines covariance between all theorized constructs. However, measurement models can also be created that align with a proposed research model in which covariance relationships are assumed to not exist. Multiple exogenous variables are assumed to not covariate. In this way, the measurement model focuses exclusively on determining how well the indicators load on the exogenous and endogenous variables. Once the measurement model was created and validated, a structural model was created based on a path diagram. The path diagram includes the dependence relationships that are proposed between the exogenous variables and endogenous variables. In a similar manner as is used to verify the measurement model, goodness of fit indicators are used to verify the structural model. All structural equation modeling work was completed using JMP 15.0.

Conclusion

Chapter 3 highlighted a research methodology approach that is consistent with traditional research agendas in the behavioral sciences. A well thought out survey instrument, informed by prior research, was developed and properly disseminated. An unbiased approach was taken to attract survey respondents. Traditional and well accepted statistical tests were performed in order to validate the theoretical model.

Chapter 4. Analysis of the Data

Chapter 4 provides a thorough statistical analysis of the data. The methodology follows a traditional data analytics process whereby the raw data is collected, appropriate data cleansing and preprocessing activities are performed, cleansed data is imported into a statistical analysis tool (in this case SAS JMP Pro 15.0) where various statistical tests are performed and results communicated. The overall methodologies, approaches, statistical tests, and evaluation of various metrics align to literature in multivariate data analysis (Hair, Black, Babin, & Anderson, 2015). As this project sought to test a theoretical model, structural equation models were created and validated. Beyond the specific statistical techniques, the analysis seeks to answer the following proposed research questions:

RQ1: What are the emergent enablers to a higher education faculty member's willingness to adopt learning analytics into their professional practice?

RQ2: What role does the concept of professional identity expectancy fill in determining a higher education faculty member's willingness to adopt learning analytics?

Part 1: Survey Instrument Analysis

Data Collection and Preprocessing

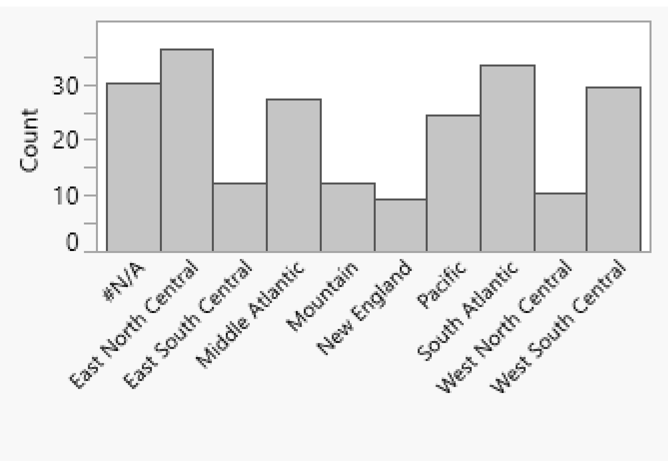
The final survey was created in Survey Monkey. Survey Monkey was also utilized for distribution and data collection. Through a pay for service to the researcher, Survey Monkey will distribute the survey to an audience whose characteristics are defined by the researcher. The broad target audience for this research project was individuals who work within the educational sector and reside in the United States. Since higher education faculty could not be individually targeted, a filter question was added to the final survey. If a survey respondent indicated they were a faculty member at a higher education institution that awards two year associates or master's degrees or four bachelor degrees or doctoral degrees, they were permitted to respond to the entire survey. Otherwise, the respondent bypassed the survey questions and were presented with a message indicating they did not qualify for the survey. All survey responses, regardless of full completion, were collected by Survey Monkey and made available for download in various formats. The collected surveys were initially downloaded from Survey Monkey into a CSV format that was later opened using Microsoft Excel 2016. A total of 1330 individual survey responses were collected. Of this total, 259 respondents indicated they were a higher education faculty member. These 259 responses represented the initial list for further analysis. However, of the 259, 37 surveys were not fully completed. These 37 were removed from future analysis leaving a total of 222 respondents. The 222 completed surveys were used in all future analysis. The initial preprocessing of the data occurred in Microsoft Excel 2016. After the total number of surveys was filtered down to the final 222, unique names were created for each individual data element. For example, DTT_01, DTT_02, DTT_03, ..., DTT_08 were given to the eight items used to measure the learning analytics tools and technology construct. This process was repeated for all items used to measure the independent and dependent constructs as well as the control variables and other demographic data collected by default in Survey Monkey. Where appropriate, numeric data was recoded as nominal data. For example, the control variable of technology adopter category was recorded in Survey Monkey as a numerical response. Utilizing VLOOKUP, the numerical response was translated into the nominal response like "Late Majority". A similar process was completed for questions like teaching discipline. If a nominal response was left unanswered by the survey respondent, #N/A was coded. Microsoft Excel was not used to aggregate any of the responses by construct. That analysis was completed in JMP.

The final surveys with recoded responses was saved and then later imported into JMP 15.0 for complete analysis.

Basic Respondent Demographic Breakdown

While not included in the theoretical model, Survey Monkey included a few basic demographic questions on the survey. These basic questions help to ensure a diversified and representative sample was achieved.

All of the respondents were from the United States. There was a fairly even regional distribution with relatively lower numbers in New England, East South Central, Mountain and West North Central (see Figure 8). There were 30 respondents that chose not to list their region. The figure is important as it shows a good cross section of regions and thereby a good cross section of multiple universities.

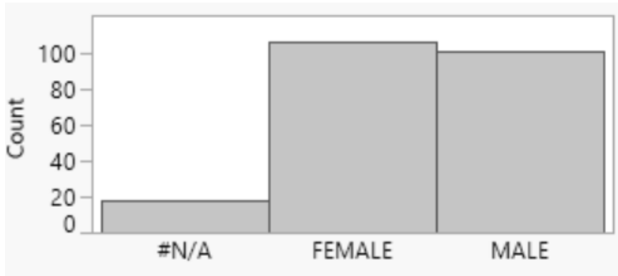


Frequencies

Level	Count	Prob
#N/A	30	0.13514
East North Central	36	0.16216
East South Central	12	0.05405
Middle Atlantic	27	0.12162
Mountain	12	0.05405
New England	9	0.04054
Pacific	24	0.10811
South Atlantic	33	0.14865
West North Central	10	0.04505
West South Central	29	0.13063
Total	222	1.00000

Figure 8. Respondent distribution by region

Of the respondents, females were slightly more likely to have completed the full survey at 47.3% vs 45% for males. 7.7% (17 individual respondents) chose not list a male or female gender designation (see Figure 9).



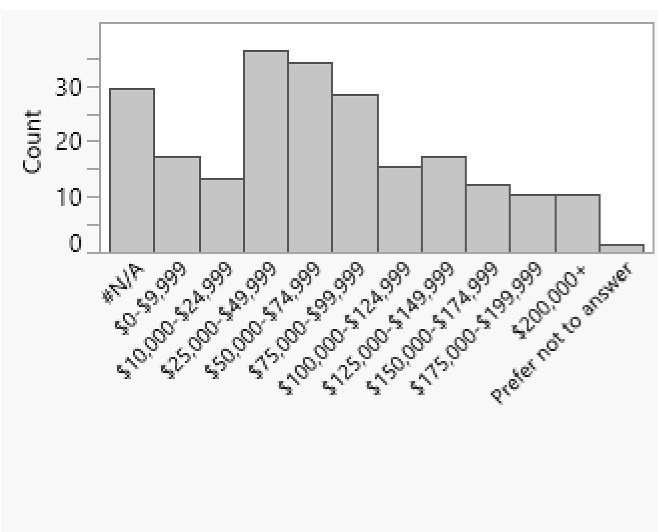
Frequencies

Level	Count	Prob
#N/A	17	0.07658
FEMALE	105	0.47297
MALE	100	0.45045
Total	222	1.00000

N Missing 0
3 Levels

Figure 9. Respondent distribution by gender

There was a relatively normal distribution for income level of the respondents (see Figure 10). Thirty respondents did not answer or responded that they preferred not answer. These figures provide further support that a good cross section of higher education faculty members completed the survey.



Frequencies

Level	Count	Prob
#N/A	29	0.13063
$0-$9,999	17	0.07658
$10,000-$24,999	13	0.05856
$25,000-$49,999	36	0.16216
$50,000-$74,999	34	0.15315
$75,000-$99,999	28	0.12613
$100,000-$124,999	15	0.06757
$125,000-$149,999	17	0.07658
$150,000-$174,999	12	0.05405
$175,000-$199,999	10	0.04505
$200,000+	10	0.04505
Prefer not to answer	1	0.00450
Total	222	1.00000

Figure 10. Respondent distribution by income level

Collectively the three figures demonstrate a diversified and representative sample of higher education faculty members.

Analysis of Construct Reliability and Validity

Each of the items within a specific theoretical construct was analyzed for uniform distribution and basic summary statistics. While not every single item displayed a perfect normal distribution, none displayed a multimodal distribution. Additionally, no item showed a heavy left or right skewness. Figures 11 through 18 provide a visual display of the respective histograms and summary statistics.

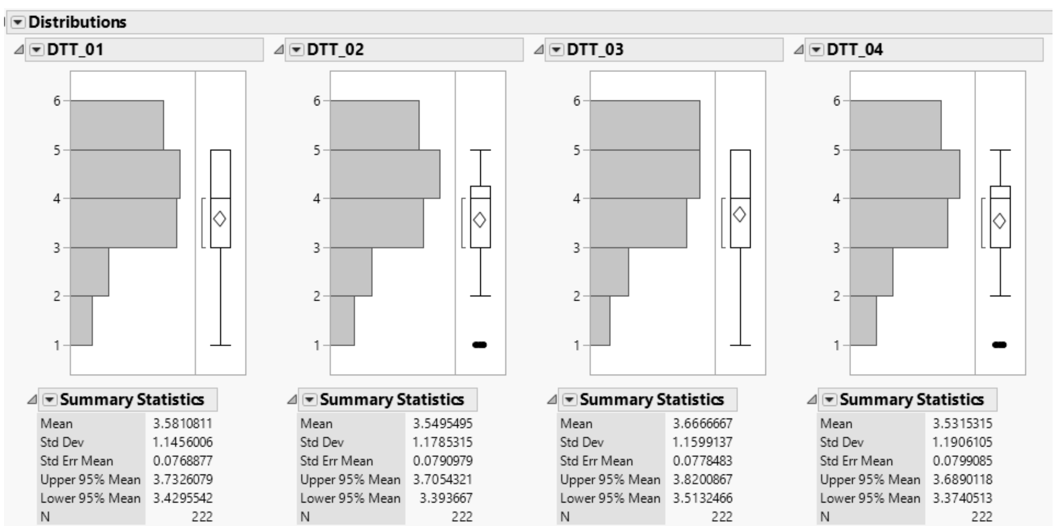


Figure 11. Learning analytics tools and technology items 1-4 distribution

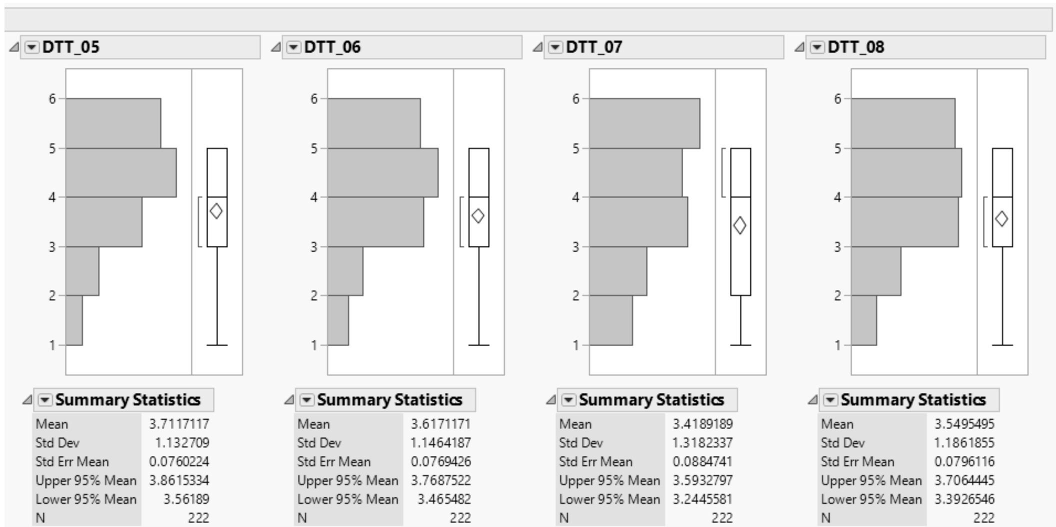


Figure 12. Learning analytics tools and technology items 5-8 distribution

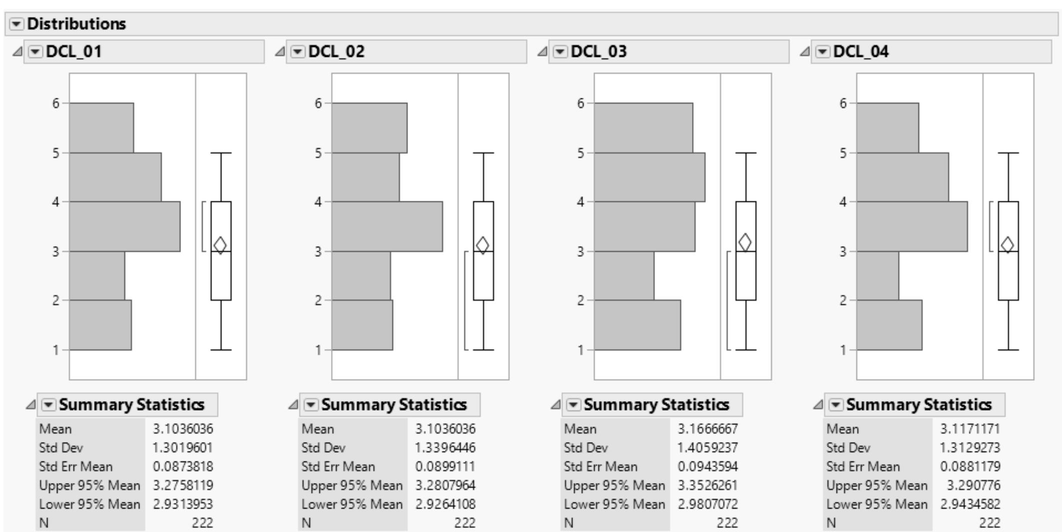


Figure 13. Data tools and technology item distribution

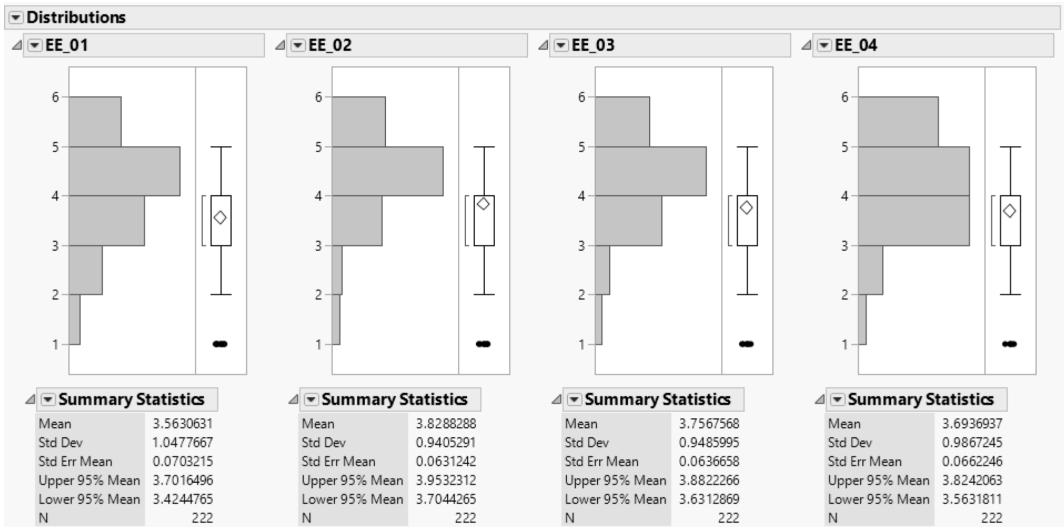


Figure 14. Effort expectancy item distribution

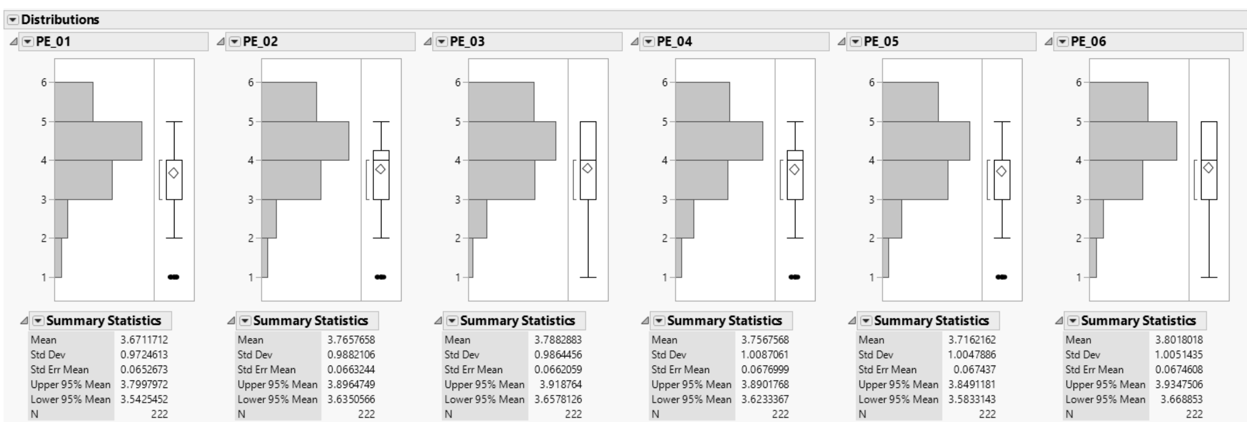


Figure 15. Performance expectancy item distribution

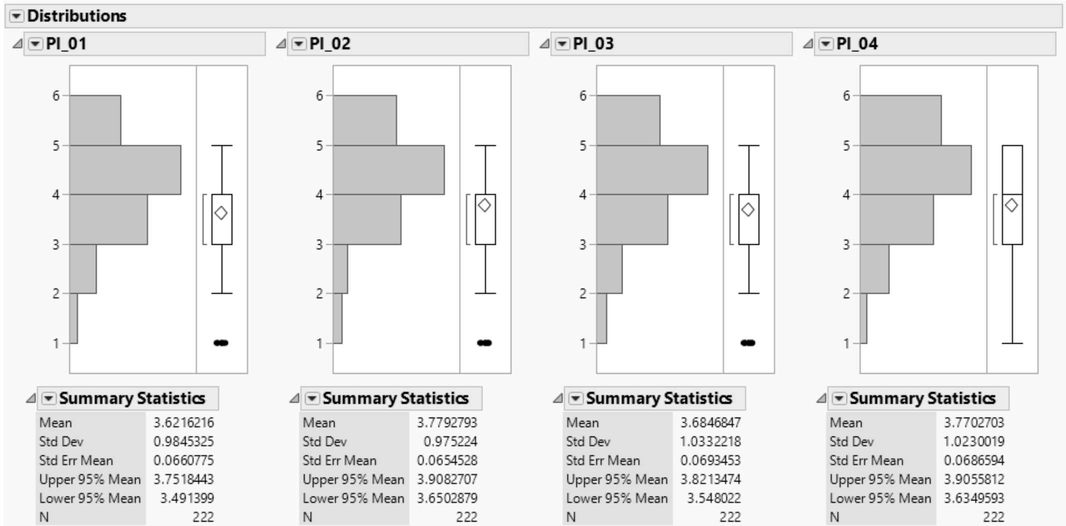


Figure 16. Professional identity expectancy item distribution

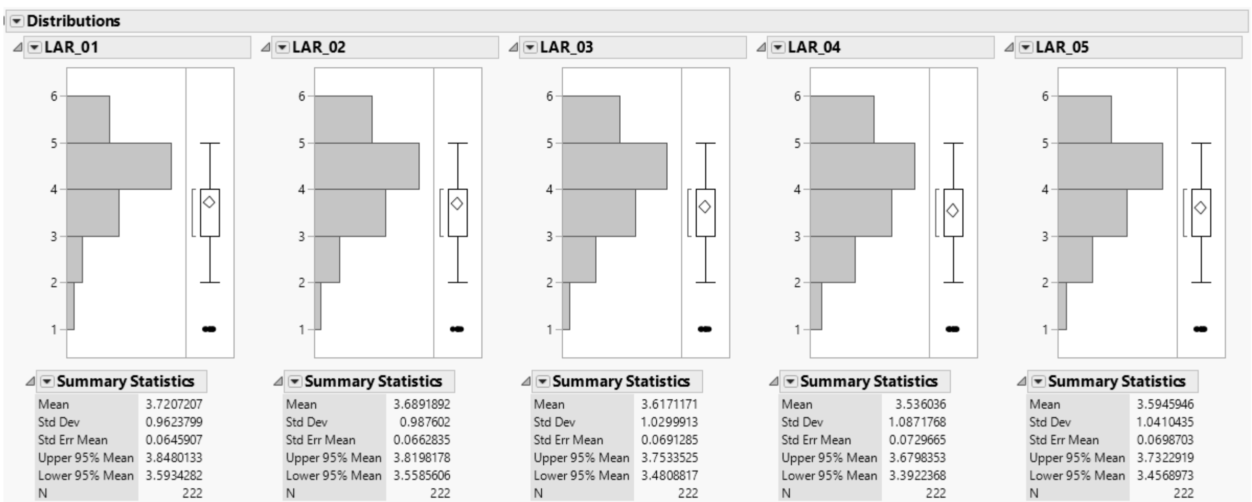


Figure 17. Perceived learning analytics readiness item distribution

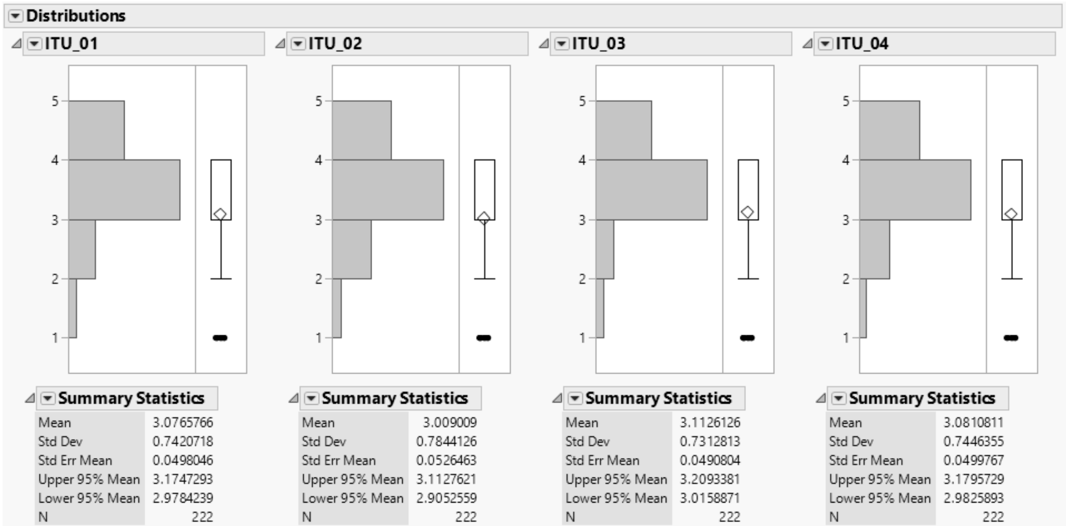


Figure 18. Willingness to adopt learning analytics item distribution

Items were analyzed for intra-construct correlations to ensure that items within a construct were highly correlated with each other. All correlations were 0.53 or greater with most being greater than 0.6. Of all the constructs, perceived learning analytics readiness displayed the weakest correlations and data cycle literacy the strongest with respect to the other constructs in the model. None of the correlations were so weak as to determine that an item should be completely removed from analysis. See Tables 2 through 8 for a breakdown of the individual item correlations within specific theoretical constructs.

Table 2. Learning analytics tools and technology item correlations

	DTT_01	DTT_02	DTT_03	DTT_04	DTT_05	DTT_06	DTT_07	DTT_08
DTT_01	1.00							
DTT_02	0.68	1.00						
DTT_03	0.68	0.71	1.00					
DTT_04	0.61	0.67	0.70	1.00				
DTT_05	0.62	0.71	0.75	0.70	1.00			
DTT_06	0.60	0.66	0.69	0.64	0.68	1.00		
DTT_07	0.56	0.67	0.73	0.64	0.63	0.67	1.00	
DTT_08	0.63	0.71	0.72	0.68	0.74	0.70	0.69	1.00

Table 3. Data cycle literacy item correlations

	DCL_01	DCL_02	DCL_03	DCL_04
DCL_01	1.00			
DCL_02	0.78	1.00		
DCL_03	0.82	0.81	1.00	
DCL_04	0.77	0.82	0.83	1.00

Table 4. Effort expectancy item correlations

	EE_01	EE_02	EE_03	EE_04
EE_01	1.00			
EE_02	0.67	1.00		
EE_03	0.66	0.71	1.00	
EE_04	0.64	0.56	0.64	1.00

Table 5. Performance expectancy item correlations

	PE_01	PE_02	PE_03	PE_04	PE_05	PE_06
PE_01	1.00					
PE_02	0.72	1.00				
PE_03	0.60	0.69	1.00			
PE_04	0.67	0.68	0.65	1.00		
PE_05	0.63	0.60	0.72	0.68	1.00	
PE_06	0.68	0.72	0.71	0.69	0.68	1.00

Table 6. Professional identity expectancy item correlations

	PI_01	PI_02	PI_03	PI_04
PI_01	1.00			
PI_02	0.57	1.00		
PI_03	0.59	0.66	1.00	
PI_04	0.62	0.65	0.66	1.00

Table 7. Perceived learning analytics readiness item correlations

	LAR_01	LAR_02	LAR_03	LAR_04	LAR_05
LAR_01	1.00				
LAR_02	0.59	1.00			
LAR_03	0.53	0.59	1.00		
LAR_04	0.55	0.54	0.62	1.00	
LAR_05	0.62	0.56	0.60	0.72	1.00

Table 8. Willingness to adopt learning analytics item correlations

	ITU_01	ITU_02	ITU_03	ITU_04
ITU_01	1.00			
ITU_02	0.70	1.00		
ITU_03	0.62	0.57	1.00	
ITU_04	0.64	0.60	0.69	1.00

Exploratory factor analysis (EFA) was performed as a preliminary step to assessing construct reliability and validity. A maximum likelihood with Varimax rotation was used when performing the factor analysis. EFA was performed with 7 identified factors in an effort to match the number of factors in the theoretical model. Table 9 shows the EFA results. Any loading greater than 0.413 is highlighted to help illustrate where items are collectively loading. Opinions seem to differ on minimum viable factor loadings. A quick Google search will find minimum thresholds as low as 0.3 with other recommended values of 0.4, 0.6 or even 0.7. Using a rule of thumb that states a EFA loading of 0.5 or greater reflects the items extract sufficient variance from the respective variable (Hair, Black, Babin, & Anderson, 2015), the data supports strong communal loadings within the constructs and relative strength of differentiation between constructs. The items measuring learning analytics tools and technology efficacy load very strongly together (all loads >= 0.5) and do not load well on other factors. Data cycle literacy exhibits very similar results. All items for learning analytics readiness load higher than 0.5 and many are closer to the more stringent value of 0.7. The items load stronger as a separate factor than associated with any other factors. Effort expectancy, performance expectancy, and professional identity expectancy did demonstrate loading on a communal factor. With the exception of one item (PE_04 factor load = 0.68), all performance expectancy loadings were 0.7 or greater. Effort expectancy loads were closer to 0.5 than 0.7, but did cluster well within a factor. All professional identity expectancy loads are 0.64 or greater which is higher the 0.5 rule of thumb and very close to the higher metric of 0.7. The dependent construct items (ITU_01...ITU_04) loaded stronger as a separate factor, but also showed some strength loading with effort expectancy, performance expectancy, and professional identity expectancy. Overall, the factor loadings support the strength of the measurement items for the individual latent constructs in the theoretical model with an observation that effort expectancy, performance expectancy, and professional identity expectancy are closely related constructs. And furthermore, these three latent constructs appear to be the ones most closely associated with willingness to adopt learning analytics. Future work may find value from additional item analysis and an effort to untangle effort, performance, and professional identity expectancy.

Table 9. Exploratory factor analysis loading results

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
DCL_01	0.318	0.427	0.662	0.176	0.071	0.108	0.188
DCL_02	0.264	0.450	0.664	0.255	0.114	0.078	-0.140
DCL_03	0.284	0.413	0.744	0.208	0.176	0.008	0.079
DCL_04	0.293	0.390	0.690	0.215	0.117	0.214	-0.062
DTT_01	0.221	0.715	0.080	0.118	0.097	0.062	0.237
DTT_02	0.202	0.784	0.124	0.143	0.128	0.083	-0.084
DTT_03	0.205	0.795	0.198	0.092	0.170	0.128	0.096
DTT_04	0.150	0.719	0.250	0.209	0.142	-0.003	0.085
DTT_05	0.209	0.773	0.188	0.113	0.139	0.077	0.008
DTT_06	0.228	0.754	0.115	0.041	0.079	0.157	-0.072
DTT_07	0.181	0.699	0.361	0.143	0.027	0.105	-0.063
DTT_08	0.219	0.779	0.203	0.228	0.069	-0.022	-0.071
EE_01	0.463	0.406	0.348	0.310	0.096	0.322	0.135
EE_02	0.457	0.287	0.179	0.204	0.207	0.542	0.027
EE_03	0.498	0.259	0.295	0.219	0.174	0.472	-0.057
EE_04	0.436	0.243	0.346	0.220	0.321	0.216	0.045
ITU_01	0.527	0.239	0.184	0.219	0.472	0.156	0.145
ITU_02	0.467	0.299	0.255	0.222	0.413	0.112	-0.028
ITU_03	0.434	0.220	0.080	0.216	0.585	0.070	-0.081
ITU_04	0.460	0.209	0.140	0.154	0.635	0.083	0.057
LAR_01	0.502	0.196	0.094	0.479	0.127	0.153	0.267
LAR_02	0.333	0.224	0.175	0.524	0.072	0.301	0.212
LAR_03	0.343	0.251	0.081	0.618	0.147	0.152	-0.152
LAR_04	0.305	0.205	0.269	0.678	0.223	-0.003	-0.060
LAR_05	0.347	0.145	0.238	0.699	0.109	0.031	0.058
PE_01	0.709	0.224	0.211	0.151	0.054	0.158	0.253
PE_02	0.720	0.286	0.112	0.223	0.157	0.185	0.050
PE_03	0.723	0.178	0.110	0.174	0.193	0.161	-0.090
PE_04	0.683	0.190	0.141	0.209	0.130	0.276	0.133
PE_05	0.704	0.131	0.220	0.183	0.209	0.040	0.130
PE_06	0.773	0.270	0.125	0.189	0.178	0.106	-0.004
PI_01	0.634	0.191	0.238	0.292	0.038	-0.144	0.008
PI_02	0.710	0.205	0.122	0.228	0.225	0.071	-0.238
PI_03	0.668	0.231	0.268	0.162	0.181	0.012	-0.052
PI_04	0.656	0.280	0.208	0.274	0.158	0.053	-0.084

While some items did exhibit cross-loading behavior, for the purposes of this study, all items were retained in the analysis and all items were left to measure the construct detailed in the theoretical model. Future research could explore these items in more detail and perhaps make changes to which items to include in data analysis. Construct measurement could also be modified slightly to select a different set of items.

With factor loadings assessed, the constructs were assessed for reliability and validity. As a first step, construct reliability was calculated using Microsoft Excel 2016. A reliability metric of 0.7 or greater tends to indicate solid reliability (Hair, Black, Babin, & Anderson, 2015). However, it is possible that construct reliability may calculate lower and still represent good reliability when compared to multiple other goodness of fit metrics (Hair, Black, Babin, & Anderson, 2015). Construct reliability measurements are presented in Table 10.

Table 10. Construct reliability measurements

Construct	Contruct Reliability
Learning Analytics Tools and Technology Efficacy	0.91
Data Cycle Literacy	0.78
Effort Expectancy	0.52
Performance Expectancy	0.87
Professional Identity Expectancy	0.76
Percieved Learning Analytics Readiness	0.74
Wilingness to Adopt Learning Analytics	0.61

As can be seen, most all constructs have a reliability score greater than 0.7. Effort expectancy presents the lowest value at 0.52 and the dependent construct of willingness to adopt learning analytics has a construct reliability measurement of 0.61. While the two reliability scores are less than 0.7, they are not completely outside the range of being considered reliable.

Construct validity can be examined across four components; convergent validity, average variance extracted (AVE), discriminant validity, and face and nomological validity (Hair, Black, Babin, & Anderson, 2015). Convergent validity describes the degree to which items converge on the specific construct they are intended to measure. The convergence can be assessed through factor loadings. Factor loadings were evaluated in a prior section of this paper. In summary, the loadings generally show high convergence (factor loading > 0.7), with some weakness of convergence in effort expectancy and willingness to adopt learning analytics. This slight weakness is also supported in the prior analysis of construct reliability. Average variance extracted was manually calculated using Microsoft Excel 2016. The results are presented in Table 11. Using a rule of thumb of 0.5 or greater to indicate acceptable convergence, it can be seen that some constructs show high convergence and others are weaker. Learning analytics tools and technology efficacy, data cycle literacy, performance expectancy, and professional identity expectancy all show adequate convergence. Effort expectancy, perceived learning analytics readiness, and willingness to adopt learning analytics do fall short of the desired threshold. It should be noted that perceived learning analytics readiness is theorized to have a moderating effect on the effect of effort and performance expectancy and not a direct effect on willingness to adopt. The relatively low AVE for willingness to adopt learning analytics may indicate that effectively measuring behavioral intention is a challenging undertaking.

Table 11. Average variance extracted measurements

Construct	AVE
Learning Analytics Tools and Technology Efficacy	0.57
Data Cycle Literacy	0.48
Effort Expectancy	0.22
Performance Expectancy	0.52
Professional Identity Expectancy	0.45
Percieved Learning Analytics Readiness	0.37
Wilingness to Adopt Learning Analytics	0.28

Discriminant validity describes the phenomena whereby each individual construct in the model is separate and distinct from other constructs in the model. Ideally each individual latent construct should measure a unique aspect of the phenomena of study. Assessing discriminant validity can start with an analysis of the construct correlations and how they compare to the average variance extracted measurements between constructs (Hair, Black, Babin, & Anderson, 2015). Strong discriminant validity is achieved if the AVE values for two constructs exceed the square of the correlation between each construct. Table 12 describes the correlations between the constructs in the theoretical model.

Table 12. Correlation matrix for theoretical constructs

	DTT_TOT	DCL_TOT	EE_TOT	PE_TOT	PI_TOT	LAR_TOT	ITU_TOT
DTT_TOT	1.00						
DCL_TOT	0.71	1.00					
EE_TOT	0.63	0.72	1.00				
PE_TOT	0.54	0.61	0.79	1.00			
PI_TOT	0.55	0.64	0.72	0.85	1.00		
LAR_TOT	0.53	0.62	0.71	0.70	0.70	1.00	
ITU_TOT	0.55	0.60	0.72	0.76	0.73	0.65	1.00

An analysis of the correlation matrix reveals that learning analytics tools and technology efficacy (DTT_TOT) is more highly correlated to data cycle literacy (DCL_TOT) than other constructs. Additionally, effort expectancy (EE_TOT), performance expectancy (PE_TOT), and professional identity expectancy (PI_TOT) are also highly correlated. And furthermore, the three correlate higher against the dependent construct of willingness to adopt (ITU_TOT) than the initial two constructs. When comparing the square of the correlations to the AVE measurements, interesting results emerge (see Table 13). The values above the diagonal are the square of the correlations between the respective constructs. The values below the diagonal are the respective

AVE values for each construct. The cells with the softest highlight indicate both AVE values are less than the square of the square of the correlations. The next darkest shading indicates one of the AVE values is greater and the other AVE value is less than the square of the correlation. The darkest shading indicates both AVE values are greater than the square the correlation. Given this shading approach, the darkest shading indicates the strongest discriminant validity and the lightest shading indicates the weakest. The data supports relatively strong discriminant validity for learning analytics tools and technology efficacy and data cycle literacy. Weaker discriminant validity is seen with effort expectancy, performance expectancy, and professional identity expectancy. The weaker discriminant validity is consistent with other statistical observations made with the data collected.

Table 13. Comparison of Square of Correlation to AVE

	DTT_TOT	DCL_TOT	EE_TOT	PE_TOT	PI_TOT	LAR_TOT	ITU_TOT	AVE
DTT_TOT	1.000	0.509	0.400	0.290	0.300	0.280	0.307	0.567
DCL_TOT	0.57, 0.48	1.000	0.524	0.371	0.404	0.384	0.362	0.477
EE_TOT	0.57, 0.22	0.48, 0.22	1.000	0.625	0.522	0.503	0.520	0.215
PE_TOT	0.57, 0.52	0.48, 0.52	0.22, 0.52	1.000	0.723	0.488	0.577	0.517
PI_TOT	0.57, 0.45	0.48, 0.45	0.22, 0.45	0.52, 0.45	1.000	0.484	0.534	0.446
LAR_TOT	0.57, 0.37	0.48, 0.37	0.22, 0.37	0.52, 0.37	0.45, 0.37	1.000	0.428	0.367
ITU_TOT	0.57, 0.28	0.48, 0.28	0.22, 0.28	0.52, 0.28	0.45, 0.28	0.37, 0.28	1.000	0.285

The correlations can also be helpful in assessing face and nomological validity. The theoretical constructs pass a face validity test in so much as they are supported through previous research and practitioner experience. Prior research, as described in a previous section of this paper, supports the role that efficacy can play in technical adoption. Additionally, foundational adoption constructs of effort expectancy and performance expectancy continue to be influential in adoption behaviors. The correlations between the constructs make intuitive sense. Effort expectancy, performance expectancy, and professional identity expectancy are distinct, but closely related concepts. Similarly, efficacy with tools and technology and the data cycle are closely related in so much as they focus on skills and knowledge. These concepts differentiate themselves from perceptions on how one might perceive their interactions with learning analytics or how one perceives the benefits of using learning analytics.

In summary, while the data does support some weaknesses as it applies to discriminant validity, the weaknesses are no so strong as to discount the entire model.

Part 2: Research Model and Hypothesis Analysis

Structural Equation Models with Analysis

A measurement model in SEM helps to determine the strength of the items as it pertains to measuring the exogenous and endogenous variables (Hair, Black, Babin, & Anderson, 2015). The sample size of 222 exceeds the minimum advised threshold for SEM. When constructing the measurement model, all variables are depicted and no regression relationships are assumed to be in place. As such, all relationships between variables are covariance relationships. The measurement model embeds a confirmatory factor analysis as all items are specifically associated to the various constructs. The measurement model was created in JMP Pro 15 and is depicted in Figure 19. The model was then “run” to assess fitness of the factors. Table 14 summarizes the goodness of fit metrics for the measurement model. As can be seen, the CFI value is near 1 at 0.92 and the RMSEA value is below 0.7 at 0.67. Both metrics give credence to an overall well fit model.

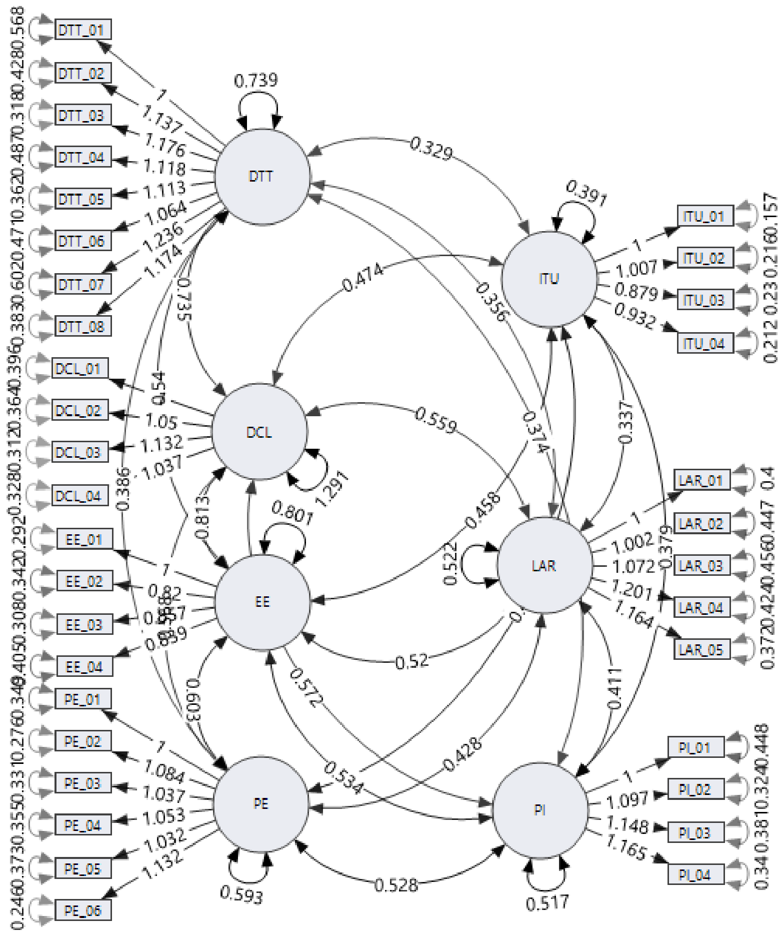


Figure 19. SEM initial measurement model

Table 14. Summary of fit metrics for the measurement model

Summary of Fit	
Converged in Gradient	
Sample Size	222
Rows with Missing	0
Iterations	5
-2 Log Likelihood	16339.782
Number of Parameters	126
AICc	16928.666
BIC	17020.519
ChiSquare	1078.2326
DF	539
Prob>ChiSq	2.768e-38
CFI	0.9202261
RMSEA	0.0671301
Lower 90%	0.0612941
Upper 90%	0.0729454

The loading estimates for confirmatory factor analysis are depicted in Table 15 and all are statistically significant.

Table 15. Measurement model loading estimates

Loadings	Estimate	Std Error	Wald Z	Prob>|Z|
DTT → DTT_01	1	.	.	.
DTT → DTT_02	1.1366651	0.0864212	13.152612	<.0001*
DTT → DTT_03	1.1756177	0.0844929	13.913812	<.0001*
DTT → DTT_04	1.118438	0.0881574	12.686826	<.0001*
DTT → DTT_05	1.1133284	0.0834088	13.347854	<.0001*
DTT → DTT_06	1.0643745	0.0851415	12.50125	<.0001*
DTT → DTT_07	1.2355828	0.0981903	12.583551	<.0001*
DTT → DTT_08	1.1737907	0.0872093	13.459474	<.0001*
DCL → DCL_01	1	.	.	.
DCL → DCL_02	1.0495221	0.0552119	19.008978	<.0001*
DCL → DCL_03	1.1324881	0.055702	20.331198	<.0001*
DCL → DCL_04	1.0368913	0.0538483	19.255775	<.0001*
EE → EE_01	1	.	.	.
EE → EE_02	0.8201345	0.05857	14.002647	<.0001*
EE → EE_03	0.8571763	0.0583983	14.678107	<.0001*
EE → EE_04	0.8391918	0.062191	13.493786	<.0001*
PE → PE_01	1	.	.	.
PE → PE_02	1.0837294	0.0740711	14.630932	<.0001*
PE → PE_03	1.0370127	0.0759398	13.655722	<.0001*
PE → PE_04	1.0533526	0.0771503	13.653248	<.0001*
PE → PE_05	1.0322467	0.0776598	13.291907	<.0001*
PE → PE_06	1.1323374	0.075184	15.060881	<.0001*
PI → PI_01	1	.	.	.
PI → PI_02	1.0972309	0.0911	12.044248	<.0001*
PI → PI_03	1.1482936	0.0961425	11.943658	<.0001*
PI → PI_04	1.1651823	0.0948061	12.290168	<.0001*
LAR → LAR_01	1	.	.	.
LAR → LAR_02	1.0019277	0.0910359	11.005851	<.0001*
LAR → LAR_03	1.0720774	0.0965042	11.10913	<.0001*
LAR → LAR_04	1.2011247	0.1028734	11.675754	<.0001*
LAR → LAR_05	1.1640337	0.0966573	12.0429	<.0001*
ITU → ITU_01	1	.	.	.
ITU → ITU_02	1.0069711	0.0707113	14.240598	<.0001*
ITU → ITU_03	0.8787366	0.0692036	12.697852	<.0001*
ITU → ITU_04	0.9320411	0.0692708	13.455044	<.0001*

Once the measurement model was created and validated, a structural model was created. The structural model includes a path diagram with the dependence and covariate relationships that are proposed between the exogenous variables and endogenous variables. Dependence relationships were created between the exogenous variables (Learning Analytics Tools and Technology, Data Cycle Literacy, Effort Expectancy, Performance Expectancy, Professional Identity Expectancy, and Perceived Learning Analytics Readiness) and the endogenous variable (Willingness to

Adopt Learning Analytics). Covariance relationships were introduced as consistent to the research model and to specifically test the interaction effect of perceived LA readiness. Additionally, in order to assess the interaction effect between Perceived Learning Analytics Readiness and Effort Expectancy and Performance Expectancy a covariance path was created between the three respective exogenous variables. Based on the path diagram, a final structural model was run and assessed for goodness of fit. The results of the path estimates are depicted in Figure 20.

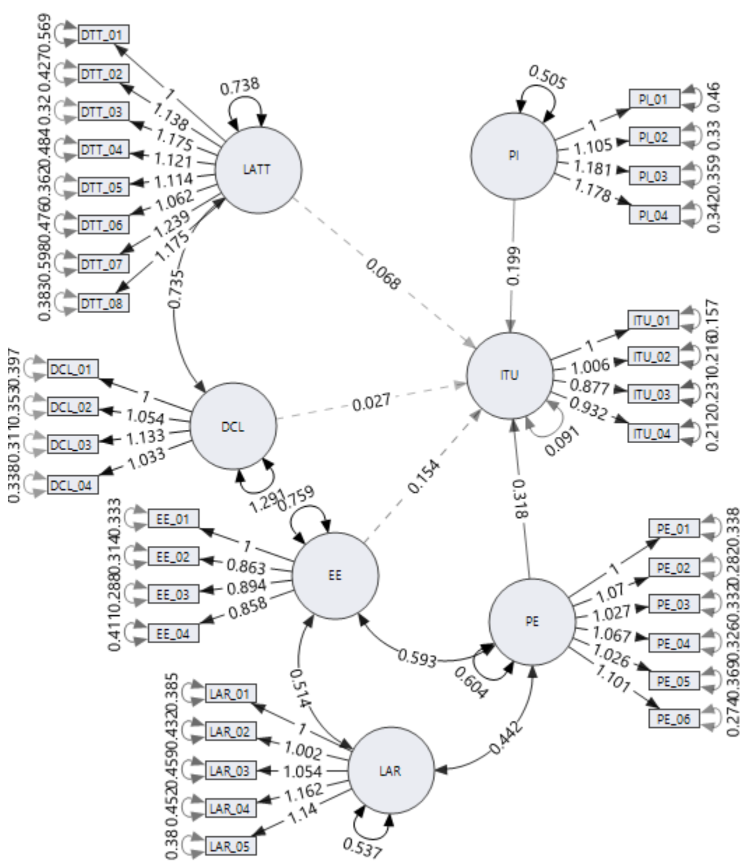


Figure 20. Path diagram for structural model

The fit indices for the structural model are depicted in Table 16. The model shows strength in places with the weakness of the model captured mostly by the weakness of the regression relationships between the efficacy constructs of LA tools and technology and data cycle literacy and the dependent construct of willingness to adopt.

Table 16. Fit indices for structural model

Fit Indices

Name	Index
-2 Log Likelihood	16854.046
AICc	17327.093
BIC	17469.951
ChiSquare	1592.4966
DF	551
Prob>ChiSq	8.52e-102
CFI	0.8459212
TLI	0.8336173
NFI	0.7834666
Revised GFI	0.7878392
Revised AGFI	0.7439439
RMSEA	0.0922734
Lower 90%	0.0870029
Upper 90%	0.0975797
RMR	0.3786982
SRMR	0.3312781

When evaluating goodness of fit, multiple rules of thumb can be utilized. The rules put forth by Hair, Black, Babin & Anderson (2015) are used for this project. While not depicted in this table, all parameter estimates were statistically significant. The ChiSquare test was also statistically significant. Based from the ChiSquare value, a normed ChiSquare can be evaluated by dividing the ChiSquare value by the degrees of freedom for the model. A ratio is thereby obtained. A ratio less than 3:1 is typically associated with a well fit model. The normed ChiSquare value for this project is 2.9:1 (1592.50 / 551). While the normed fit index (NFI) is not used as much in recent research projects (Hair, Black, Babin, & Anderson, 2015), it can still provide valuable insight.

The NFI value for this research project is 0.78, which indicates a good fit. The comparative fit index (CFI) is similar to NFI. CFI values approaching 1 indicate a well fit model and this project has a CFI value of 0.85. In a similar vein, the revised goodness of fit index (Revised GFI) and the revised adjusted goodness of fit indexes (Revised AGFI) for this project do not exceed 0.9, but are close with values of 0.79 and 0.74 respectively. The root square mean error of approximation (RMSEA) is 0.092, which is just slightly higher than the guidelines of 0.05 to 0.08 range of acceptability for well fit models. Moreover, there is a 90% confidence threshold of the RSMEA being between 0.087 and 0.098. The root mean square residual (RMR) and the standardized root mean square residual (SRMR) are above the ideal threshold of 0.1. Taken in totality, the collection of goodness of fit measures indicate the measurement model is relatively strong and gives credence to a potentially strong theoretical model. The covariance relationship between effort expectancy and perceived LA readiness is positive and statistically significant. The same is true for the covariance relationship between performance expectancy and perceived LA readiness. Future research opportunities exist to rethink the inclusion of efficacy in the LA adoption model and to analyze the interaction effect of perceived LA readiness. It is possible that perceived LA readiness functions more to as a predictor variable than an interaction variable.

The results of the model indicate that the relationship between Learning Analytics Tools and Technology and Willingness to Adopt is not as strong as what is seen with Effort Expectancy, Performance Expectancy, and Professional Identity Expectancy. The same issue is seen with Data Cycle Literacy. The loading estimates of the items are all statistically significant in this model; see Table 17.

Table 17. Loading estimates for structural model

Loadings	Estimate	Std Error	Wald Z	Prob>|Z|
LATT → DTT_01	1	.	.	.
LATT → DTT_02	1.1382444	0.0865754	13.14744	<.0001*
LATT → DTT_03	1.1753821	0.0846723	13.881549	<.0001*
LATT → DTT_04	1.1208244	0.0883043	12.692746	<.0001*
LATT → DTT_05	1.1139594	0.0835767	13.328595	<.0001*
LATT → DTT_06	1.0620693	0.0853027	12.45059	<.0001*
LATT → DTT_07	1.2389161	0.0983586	12.595906	<.0001*
LATT → DTT_08	1.1746979	0.087362	13.446327	<.0001*
DCL → DCL_01	1	.	.	.
DCL → DCL_02	1.0538335	0.0553045	19.055117	<.0001*
DCL → DCL_03	1.132828	0.0559249	20.256232	<.0001*
DCL → DCL_04	1.0331818	0.0542977	19.028103	<.0001*
EE → EE_01	1	.	.	.
EE → EE_02	0.8634604	0.0620861	13.907471	<.0001*
EE → EE_03	0.8942668	0.0625105	14.305875	<.0001*
EE → EE_04	0.8576602	0.0664849	12.900074	<.0001*
PE → PE_01	1	.	.	.
PE → PE_02	1.0697416	0.0730749	14.638965	<.0001*
PE → PE_03	1.0267854	0.0753441	13.627944	<.0001*
PE → PE_04	1.0667059	0.0757273	14.086149	<.0001*
PE → PE_05	1.0264831	0.0768927	13.34956	<.0001*
PE → PE_06	1.1009089	0.0746942	14.738872	<.0001*
PI → PI_01	1	.	.	.
PI → PI_02	1.1048855	0.1003263	11.012922	<.0001*
PI → PI_03	1.1806619	0.1056779	11.172269	<.0001*
PI → PI_04	1.17757	0.1030657	11.425429	<.0001*
LAR → LAR_01	1	.	.	.
LAR → LAR_02	1.0018311	0.0887638	11.286481	<.0001*
LAR → LAR_03	1.0541415	0.0941986	11.190626	<.0001*
LAR → LAR_04	1.1615973	0.1000592	11.609101	<.0001*
LAR → LAR_05	1.1402805	0.0941147	12.115862	<.0001*
ITU → ITU_01	1	.	.	.
ITU → ITU_02	1.0062622	0.0706746	14.237959	<.0001*
ITU → ITU_03	0.8772599	0.0691911	12.678799	<.0001*
ITU → ITU_04	0.932323	0.0692269	13.467635	<.0001*

The regression estimates are depicted in Table 18. The regression estimates for Learning Analytics Tool and Technology, Data Cycle Literacy, and Effort Expectancy do not report as statistically significant. However, Effort Expectancy is nearly significant with the Prob>|Z| = 0.11. The results seem to indicate that efficacy with the learning analytics tools is not as influential as effort, performance, or professional identity expectancy as it pertains to predicting willingness to adopt learning analytics.

Table 18. Regression estimates in structural model

Regressions	Estimate	Std Error	Wald Z	Prob>|Z|
LATT → ITU	0.0675314	0.052624	1.283281	0.1994
DCL → ITU	0.0268685	0.0451855	0.5946276	0.5521
EE → ITU	0.1540441	0.0979289	1.57302	0.1157
PE → ITU	0.3177671	0.1184802	2.6820284	0.0073*
PI → ITU	0.1991798	0.083837	2.3757988	0.0175*

The covariance estimate between Perceived Learning Analytics Readiness and Effort Expectancy is positive (0.514) and statistically significant. Similarly, the covariance estimate between Perceived Learning Analytics Readiness and Performance Expectancy is positive (0.442) and statistically significant. This gives credence to theorized interaction effect. See Table 19.

Table 19. Covariance estimates in structural model

Covariances	Estimate	Std Error	Wald Z	Prob>|Z|
EE ↔ LAR	0.5143388	0.0700424	7.3432456	<.0001*
LAR ↔ PE	0.442017	0.0619654	7.1332916	<.0001*
LATT ↔ DCL	0.7346093	0.0986555	7.4462058	<.0001*
EE ↔ PE	0.5928552	0.0743134	7.9777713	<.0001*

Figure 21 is a visualization to help evaluate the strength of the interaction effect of perceived LA readiness on the relationship between effort expectancy and willingness to adopt. The figure depicts effort expectancy along the x-axis and willingness to adopt LA along the y-axis. Additionally, the graph is partitioned by binning the total perceived LA readiness scores. The graphs provides early support for the notion that willingness to adopt scores will be higher for individuals that show relatively equal effort expectancy scores, but demonstrate a higher perceived LA readiness score.

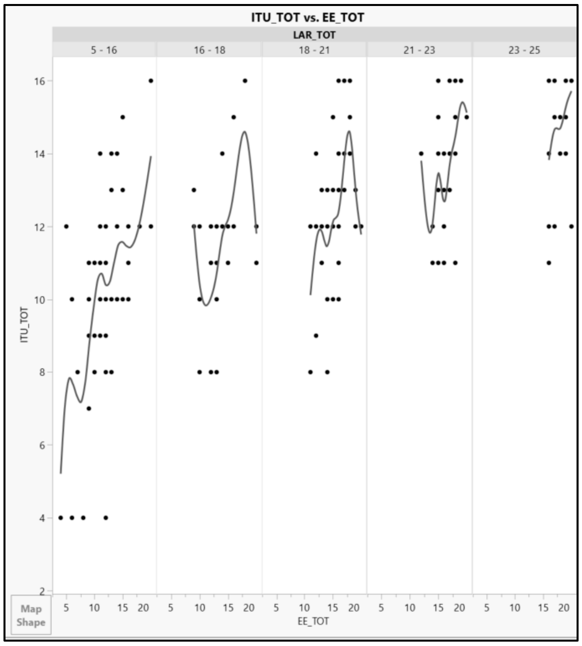


Figure 21. Influence of LAR on EE and ITU

In a similar fashion, Figure 22 helps to evaluate the strength of the interaction effect of perceived LA readiness on the relationship between performance expectancy and willingness to adopt. Here again, the data provides early support for the notion that perceived LA readiness increases the willingness to adopt behavior within individuals of similar performance expectancy scores.

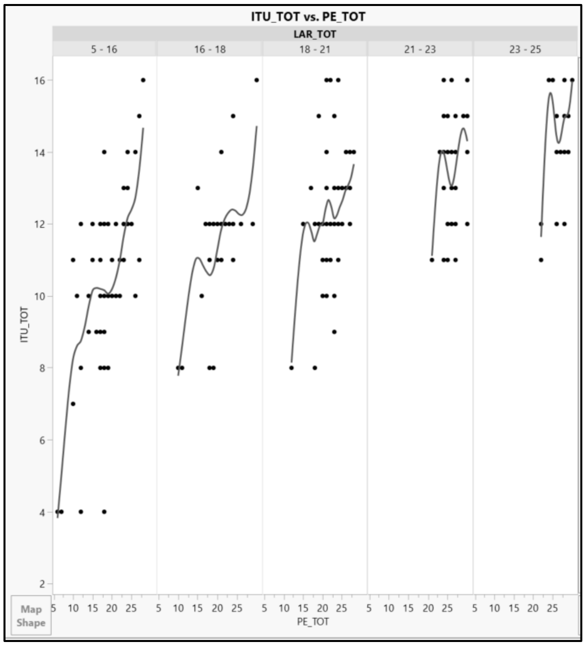
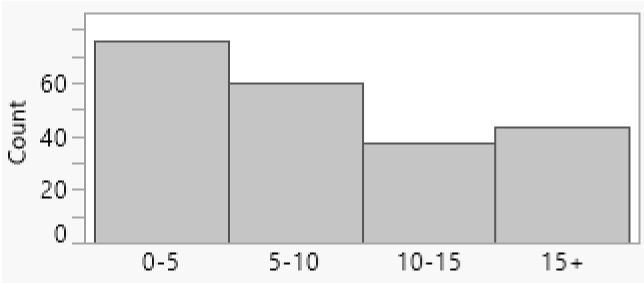


Figure 22. Influence of LAR on PE and ITU

Analysis of Control Variables in the Theoretical Model

Several control variables are included in the theoretical model: teaching experience, teaching discipline, adopter category, propensity to incorporate external feedback, and current analytics user. It is possible that barring all other independent constructs, these control variables influence a higher education faculty member's willingness to adopt learning analytics.

Years of teaching experience did show slight variations as it pertains to willingness to adopt. Of the 222 respondents, 8 chose not answer the years of service question. Of the remaining 214, there was a general even distribution across the bins (see Figure 23). The 0-5 years of experience bin had slightly more respondents at 75.



Frequencies

Level	Count	Prob
0-5	75	0.35047
5-10	59	0.27570
10-15	37	0.17290
15+	43	0.20093
Total	214	1.00000

N Missing 8

Figure 23. Respondent distribution by years of teaching experience

The dependent construct was measured using the following four items.

ITU_01: I hope to use learning analytics in the coming academic year.

ITU_02: I intend to use learning analytics in the coming academic year.

ITU_03: I hope to use learning analytics in the next 2-5 years.

ITU_04: I intend to use learning analytics in the next 2-5 years.

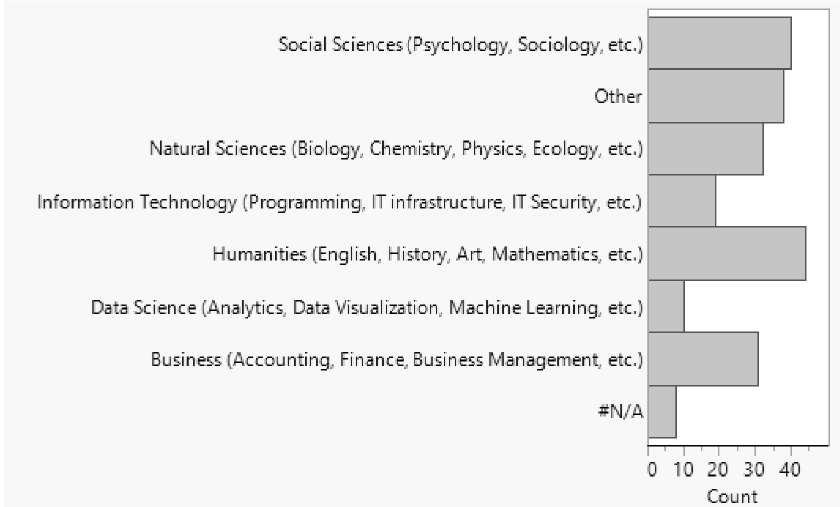
Items ITU_01 and ITU_03 measure hopeful intent while ITU_02 and ITU_04 measure purposeful intent. The items were measured using a 4 point Likert scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Agree, and 4 = Strongly Agree. Table 20 shows the comparison of means of each item across the various years of teaching experience bins. A total for all items was calculated by summing the four items and has been labeled ITU_TOT.

Table 20. Comparison of intention to adopt LA by years of service

	ITU_01	ITU_02	ITU_03	ITU_04	ITU_TOT
YRS_SVC_CATEGORY	Mean	Mean	Mean	Mean	Mean
0-5	3.12	3.04	3.08	3.04	12.28
5-10	3.24	3.20	3.34	3.20	12.98
10-15	3.00	3.00	3.24	3.19	12.43
15+	2.93	2.84	2.77	2.91	11.44

While the results are similar across the bins, trends do emerge. For relatively inexperienced higher education faculty, 0-5 years of experience, they demonstrate more hopeful intention than purposeful intention. The means for ITU_01 and ITU_03 are 3.12 and 3.08 respectively as compared to 3.04 for ITU_02 and ITU_04. Faculty with 5-10 years of experience demonstrate a stronger hopefulness for long term future use vs short term. This group also demonstrates the strongest aggregate mean for intention to use with a value of 12.98. An interesting observation with the faculty having 10-15 years of service is that while they average 3.00 for short term intention (next academic year), they demonstrate a much stronger intention for the future (2-5 years). This could indicate an intention to deepen their usage of learning analytics into their professional practice. The most senior group of faculty, those with 15+ years of teaching experience, record slightly less intention to use learning analytics. They comparatively report the lowest mean scores. And their total mean score is the smallest amongst the four groups. This could indicate faculty in this group are set in their methodologies and less likely to adopt new technologies like learning analytics into their professional practice.

Respondents were asked to categorize their primary teaching discipline. Six specific disciplines were presented along with an “other” category. Of the 222 respondents, 8 did not provide an answer to the teaching discipline question. The distribution of the disciplines is depicted in Figure 24. The distribution is relatively even across the disciplines with a slightly less representation from Information Technology and Data Science. Overall, the distribution indicates a good cross section of different teaching disciplines which provides further evidence of a representative sampling of higher education faculty.



Frequencies

Level	Count	Prob
#N/A	8	0.03604
Business (Accounting, Finance, Business Management, etc.)	31	0.13964
Data Science (Analytics, Data Visualization, Machine Learning, etc.)	10	0.04505
Humanities (English, History, Art, Mathematics, etc.)	44	0.19820
Information Technology (Programming, IT infrastructure, IT Security, etc.)	19	0.08559
Natural Sciences (Biology, Chemistry, Physics, Ecology, etc.)	32	0.14414
Other	38	0.17117
Social Sciences (Psychology, Sociology, etc.)	40	0.18018
Total	222	1.00000

Figure 24. Distribution of respondents by primary teaching discipline

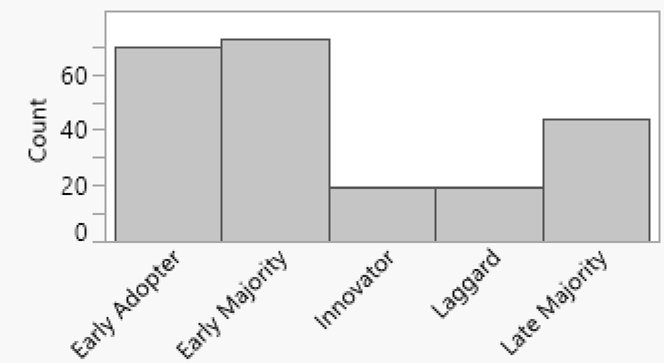
Using a similar analysis strategy as previous documented, the means for the dependent construct were tabulated across the different teaching disciplines (see Table 21). An immediate result of note is the comparatively higher total mean scores for faculty teaching in Data Science and Information Technology. The mean score for the Data Analytics group was 14.7 out a highest possible score of 16. It is difficult to know with specificity what are the various disciplines involved in “Other”. However, it is worthy of note that this category reported the lowest aggregate mean score when ignoring the 8 respondents who left this question blank. The data supports respondents are slightly more hopeful in their intent than they are committed in their intent. An example of this is evidenced by reviewing mean ITU scores for Humanities. The first and third items score hopeful intention and have means scores of 3.07 and 2.95 respectively. The second and fourth mean scores measure committed intention and have values of 2.82 and 2.93 respectively. Another example is seen with the Natural Sciences group. An examination of the third and fourth items (intention in the next 2-5 years) shows that group is more hopeful (mean = 3.16) than committed (mean = 3.06). It is also interesting to note that most all groups report higher mean scores for future intention versus current intention. The first and second items focus on the current academic year, while the third and fourth items focus on the future 2-5 years.

Table 21. Comparison of willingness to adopt by teaching discipline

	ITU_01	ITU_02	ITU_03	ITU_04	ITU_TOT
TEACH_DISC_TEXT	Mean	Mean	Mean	Mean	Mean
#N/A	2.63	2.25	3.00	3.00	10.88
Business (Accounting, Finance, Business Management, etc.)	3.13	3.10	3.16	3.16	12.55
Data Science (Analytics, Data Visualization, Machine Learning, etc.)	3.60	3.70	3.80	3.60	14.70
Humanities (English, History, Art, Mathematics, etc.)	3.07	2.82	2.95	2.93	11.77
Information Technology (Programming, IT infrastructure, IT Security, etc.)	3.37	3.47	3.37	3.32	13.53
Natural Sciences (Biology, Chemistry, Physics, Ecology, etc.)	3.00	3.03	3.16	3.06	12.25
Other	2.76	2.71	2.79	2.84	11.11
Social Sciences (Psychology, Sociology, etc.)	3.23	3.18	3.25	3.20	12.85

Technology diffusion can be influenced by an individual’s approach to technology adoption (Rogers, 1983). For this study, each respondent was asked to report their self-assessed approach to technology adoption. This is an important control variable because barring all other factors, the most critical factor involved in determining a higher education faculty member’s willingness to adopt learning analytics may simply lie in their own behaviors and attitudes towards adoption of novel tools and processes. The distribution shows more respondents fell into the Early Adopter or Early Majority category than the other three (see Figure 25). This may be partially explained because teachers tend to be exploratory by nature. There were a number of Late

Majority respondents (n = 43) and while an initial explanation might be these individuals represent the more tenured faculty, the data does not support such a conclusion (see Table 22).



Frequencies

Level	Count	Prob
Early Adopter	69	0.31081
Early Majority	72	0.32432
Innovator	19	0.08559
Laggard	19	0.08559
Late Majority	43	0.19369
Total	222	1.00000

N Missing 0
5 Levels

Figure 25. Distribution of respondents by adoption acceptance category

Table 22. Distribution of technology adoption category by years of service

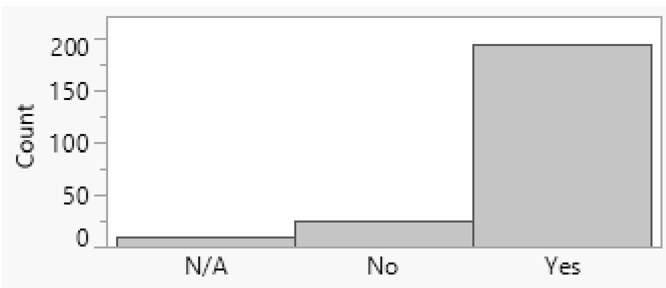
	TECH_ADOPT_TEXT				
YRS_SVC_CATEGORY	Early Adopter	Early Majority	Innovator	Laggard	Late Majority
0-5	23	22	7	8	15
5-10	18	16	7	6	12
10-15	10	19	1	2	5
15+	17	12	3	2	9

Very interesting, and perhaps predictable, trends start to emerge when the technology adoption categories are compared against the mean scores for the willingness to adopt construct items (see Table 23). Note that the Innovator category has been moved to the top of the list in order to properly represent the spectrum of adoption tendencies. Within that spectrum, innovators precede early adoption and often exist on the cutting edge of technology implementation. The Late Majority that exists on the other end of the spectrum sees very late adoption, or even full resistance to adoption. The mean score for each item, as well as the aggregate total, exhibit a linear trend downward. The innovators have the highest mean score for the total at 13.95 and the late majority shows a much smaller mean at 10.70. The data supports the notion that willingness to adopt learning analytics into one's professional practice is highly influenced by how that individual self identifies their adoption beliefs and behaviors.

Table 23. Comparison of willingness to adopt by technology adoption category

TECH_ADOPT_TEXT	Mean(ITU_01)	Mean(ITU_02)	Mean(ITU_03)	Mean(ITU_04)	Mean(ITU_TOT)
Innovator	3.53	3.47	3.42	3.53	13.95
Early Adopter	3.26	3.17	3.23	3.13	12.80
Early Majority	3.04	3.06	3.10	3.25	12.44
Laggard	3.00	2.84	3.05	2.79	11.68
Late Majority	2.67	2.53	2.84	2.65	10.70

Learning analytics represents a form of pedagogical feedback. Through learning analytics a higher education faculty garners a deeper insight into effectiveness of pedagogical practices and possibly a deeper understanding of the student experience. This type of feedback has traditionally come through course evaluations and student feedback surveys. A control variable was added to the theoretical model to help determine how willingness to adopt learning analytics might be influenced by how a higher faculty member uses, or doesn't use, traditional external reviews such as a student feedback survey. Most all respondents, 192 of the 222 (86.5%) indicated they did use such surveys (see Figure 26). 23 respondents indicated they did not tend to use external feedback such as student surveys and only 7 reported that their university does not use student feedback surveys. On the surface this would indicate that most all higher education faculty would be willing to adopt learning analytics since some learning analytics are just a different form of student feedback. And in fact, intention to use does vary based on how the higher education faculty member incorporates student feedback (see Table 24). Higher education faculty members who reported "Yes" on the question about tendency to use external feedback such as student surveys had a mean total intention to use learning analytics score of 12.51 as compared to the group that answered "No" who score 10.48. The data supports the notion that if higher education faculty do not currently utilize student feedback surveys or course evaluations, they are very much less likely to incorporate modern feedback tools such as learning analytics into their professional practice.



Frequencies

Level	Count	Prob
N/A	7	0.03153
No	23	0.10360
Yes	192	0.86486
Total	222	1.00000

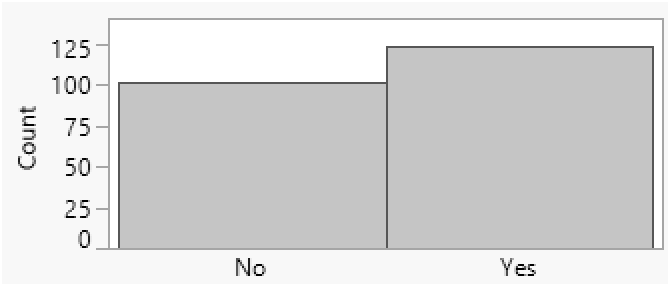
N Missing 0
3 Levels

Figure 26. Respondent distribution by tendency to use external feedback (student surveys)

Table 24. Comparison of willingness to adopt LA by student feedback usage

	ITU_01	ITU_02	ITU_03	ITU_04	ITU_TOT
STD_FEEDBACK_TEXT	Mean	Mean	Mean	Mean	Mean
N/A	3.29	3.00	3.14	2.57	12.00
No	2.70	2.61	2.52	2.65	10.48
Yes	3.11	3.06	3.18	3.15	12.51

While most faculty (86.5%) use traditional student feedback surveys, only 55% currently use learning analytics in their profession practice (see Figure 27). The data supports the trend that learning analytics adoption in higher education institutions is still emerging and has not yet reached saturation. When current usage of learning analytics is compared to years of service, large opportunities present themselves for the relatively inexperienced faculty member (see Table 25). This is a somewhat surprising result as it is reasonable given that less experienced faculty reported higher scores on the Early Adopter and Early Majority adoption spectrum. Perhaps learning analytics and usage is learned on the job and takes several years to understand and fully incorporate into professional practice. A future longitudinal study in learning analytics may help to answer such a question.



Frequencies

Level	Count	Prob
No	100	0.45045
Yes	122	0.54955
Total	222	1.00000

N Missing 0
2 Levels

Figure 27. Respondent distribution by current user of learning analytics

Table 25. Current user of learning analytics by years of service

	CURR_USE_TEXT	
YRS_SVC_CATEGORY	No	Yes
0-5	40	35
5-10	19	40
10-15	16	21
15+	20	23

When intention to use learning analytics is measured across current usage behavior, dramatic differences emerge (see Table 26). The data supports the notion that if individuals are not currently adopting learning analytics into their professional practice, they are much less likely to adopt in the future. The data suggests that initiation may be a unique challenge to adoption. For once a higher education faculty does cross that threshold and does begin to incorporate learning analytics, they appear to be much more willing to continue using them. This suggests perceived value in the learning analytics. Here again, a longitudinal study would add value for understanding how higher education faculty continue to grow with learning analytics over time and what perhaps influences them to stop using analytics after they have started.

Table 26. Comparison of willingness to adopt LA by current usage of LA

	ITU_01	ITU_02	ITU_03	ITU_04	ITU_TOT
CURR_USE_TEXT	Mean	Mean	Mean	Mean	Mean
No	2.74	2.68	2.86	2.83	11.11
Yes	3.35	3.28	3.32	3.29	13.24

Conclusion

Chapter 4 highlighted the analysis the final survey data. The data supports a survey instrument that is well constructed and statistically validated. The number of respondents was strong and the variability of the results allowed for fruitful analysis. Overall the data supports a well formed model shows support for some of the theorized hypotheses, but not all. Many insights are obtained from the analysis of the survey responses.

Chapter 5. Discussion

An outcome of this research includes a clearer picture of how the emergent culture of learning analytics in HEIs is perceived by the faculty member and more specifically how faculty reconcile this culture against their views of their own professional identity. In tangent to this outcome, the research highlights challenges and opportunities of aligning learning analytics culture to the professional identity of educators. Practitioners can benefit from such insights. A clearer picture of the true cultural state of analytics affects their ability to fulfill strategic and operational tasks. Additionally, knowledge in this area adds to the body of knowledge in organizational culture and technology adoption by revealing how an individual best incorporates data and analytics into their professional lives. This research yields insights into the role that an analytics culture plays in an organization's ability to achieve strategic and operational objectives and possibly uncover unintended consequences of said culture. This outcome centers on the assumption that a HEI is overtly working to achieve a more data-centric supported decision-making model. Knowledge such as this is valuable to both practitioners and the research community. The research extends the level of understanding of the role of organizational culture because a new culture of analytics is emerging. A comprehensive understanding of the impact of an analytics culture on the individual educator does not yet exist. Lastly, the research provides for a deeper understanding of the success factors and barriers for adopting a culture of analytics. This is perhaps the most valuable insight. As HEIs race to adopt a culture of analytics, they struggle to understand the critical success factors to implement such organizational change. They are also insensitive to potential barriers. Lack of understanding in both areas contributes to an elongated and tumultuous change process. This change process must in part focus on the impact to the individual educator. The individual faculty member sits at the center of the learning analytics culture. This research agenda benefits an employee centric view of learning analytics usage.

Summary of Findings

There were two principle research questions that guided this study.

> RQ1: What are the emergent enablers to a higher education faculty member's willingness to adopt learning analytics into their professional practice?
>
> RQ2: What role does the concept of professional identity expectancy fill in determining a higher education faculty member's willingness to adopt learning analytics?

Enablers to willingness to adopt include beliefs or situations that are highly correlated to willingness to adopt. The data supports that effort expectancy and performance expectancy are enablers. If higher education faculty perceive the cognitive load of using LA to be relatively low, they are more likely to adopt LA into their professional practice. In a similar fashion, if faculty believe that LA will improve their performance, they are more likely to be willing to adopt. The data did not support an individual's efficacy with LA tools and technology to be highly influential on willingness to adopt. Belief in one's own ability and understanding of using LA was not as important as believing the tools to be easy to use or helpful in improving performance. This is actually a positive outcome. LA is still emerging and as such, relatively few faculty will have high understanding or efficacy with the tools. The data in this study supports the idea that low efficacy will not prove to be a barrier to adoption. The same is true for data cycle efficacy. While the data cycle is a foundational theory for LA, the data did support efficacy with the data cycle was highly influential in willingness to adopt. This is akin to the metaphor that lack of understanding about an internal combustion engine is not a deterrent to individuals wanting to learn how to drive a car.

Evaluation of Hypotheses

Recall hypothesis 1.1 and 1.2.

> H 1.1: The stronger a higher education faculty member perceives their efficacy with learning analytics tools and technology, the more willing they will be to adopt learning analytics into their professional practice.
>
> H 1.2: The stronger a higher education faculty member perceives their literacy with the data cycle, the more willing they will be to adopt learning analytics into their professional practice.

The analysis provided by structural equation modeling does not support these two hypotheses. The data does not proport that the stronger a higher education faculty member scored in areas of LA efficacy, the stronger their reported willingness to adopt LA. Future work in LA adoption may benefit from a deeper review of efficacy and how higher education institutions are supporting faculty as they begin to navigate learning analytics utilization.

Hypotheses 2.1 and 2.2 focused on effort expectancy and performance expectancy. These are critical dimensions of previous work in LA adoption (Venkatesh, Morris, Davis, & Davis, 2003).

> H 2.1: The higher the effort expectancy (ease of use) as perceived by the higher education faculty member, the more willing they will be to adopt learning analytics into their professional practice.
>
> H 2.2: The higher the performance expectancy as perceived by the higher education faculty member, the more willing they will be to adopt learning analytics into their professional practice.

The data collected does provide support for both hypotheses. The path estimates were positive and statistcially significant. This supports foundational work in technology adoption and provides evidence that traditional technology adoption theory stills has applications in the modern era and specifically within the LA space.

This research extended traditional technology adoption theory by including professional identity alignment in the model. Hypothesis 3.1 captures this extension.

> H 3.1: The higher the professional identity expectancy as perceived by the higher education faculty member, the more willing they will be to adopt learning analytics into their professional practice.

The analysis supports hypothesis 3.1. The path estimate was positive and significant. The data supports professional identity alignment being closing linked to effort expectancy and performance expectancy. It appears that all three concepts speak to an underlying notion that higher education faculty are drawn to using tools that align with their practice, relatively easy to use, and likely support improved professional performance.

The research project also investigated the influencing role that perceived LA readiness has on LA adoption. Specifically, the research investigate the role it plays on the effort expectancy and performance expectancy influence. This is captured within hypotheses 4.1 and 4.2.

> H 4.1: Perceived institutional learning analytics readiness will moderate the relationship between effort expectancy and willingness to adopt. The moderated relationship is hypothesized to strengthen the relationship such that the higher the perceived institutional learning analytics readiness, the stronger the effect will be on willingness to adopt.
>
> H 4.2: Perceived institutional learning analytics readiness will moderate the relationship between performance expectancy and willingness to adopt. The moderated relationship is hypothesized to strengthen the relationship such that the higher the perceived institutional learning analytics readiness, the stronger the effect will be on willingness to adopt.

The data does provide support for both hypotheses. The covariance estimates were both positive and statistically significant. This supports the notion that the stronger a higher education faculty member perceives their institutional readiness, the greater the influence of effort expectancy and performance expectancy. Stated differently, perceived learning analytics readiness will strengthen the positive relationship that effort expectancy and performance expectancy has on willingness to adopt learning analytics.

Summarization of Control Variable Findings

By and large the data supported faculty being more hopeful than intentional as it pertains to willingness to adopt learning analytics. Faculty with longer years of service were slightly less willing to adopt than their less experienced counterparts. Faculty who teach in data science and technology related fields are more willing to adopt than others. This in part may be explained by their comfort level with the tools and the general culture of data driven decision making. Although that does run orthogonal to the data the supports low influence of efficacy of tools. However, for individuals who teach in data science or technology related fields, their personal conceptualization of their professional identity may run closer to the goals of LA and as such, their adoption behavior differs. Perceptions of one’s own technology adoption behavior shows to be highly influential in LA adoption behavior. As might be predicted, individuals who classify themselves as Early Adopters are much more likely to adopt LA than are individuals who classify themselves as Laggards. The data reported for using external feedback such as student surveys was highly skewed towards the “yes” response. However, given the relatively low number of no’s, the data still supports the notion that individuals who are less likely to use external feedback such as student surveys, are also much less likely to be willing to adopt LA. And finally, as might be expected, if an individual is a current user of LA, they are much more likely to be willing to use analytics in the future. It should be noted, then even for individuals who do not currently use analytics, there appears to still be a relative interest and curiosity in integrated LA into their professional practice. Future research may investigate where the tipping point is from non-adoption to adoption. It would be interesting to uncover what the influential factors are that ultimately sway an individual into incorporating LA into their professional practice.

The data in large part supports the notion that higher education faculty tend to be more hopeful than committed to adopting LA into their professional practice.

Implications and Recommendations

The results indicate that effort expectancy, performance expectancy, and professional identity expectancy play a vital role in predicting willingness to adopt LA. Furthermore, the data supports the notion that perceived LA readiness has an interaction effect on the influence of effort expectancy and performance expectancy. The data does not support LA tools and technology efficacy and data cycle literacy being an influential factor on LA adoption. Much of the results of the current study are in line with recent research into adoption of predictive learning analytics (PLA) dashboards (Herodutou, Maguire, Hlosta, & Mulholland, 2023). UTAUT was used as the foundational adoption theory for the referenced study and the researchers found positive support for the influence of performance expectancy and facilitating conditions on the behavioral intention to use the dashboard. Unlike the current study, the PLA research found positive support for the role of self-efficacy and a negative influence of effort expectancy. This discrepancy showcases that influencing factors on technology adoption may be highly situational and technology specific. It is also worth noting that the PLA research draws specific attention to the importance of training, easy to use and comprehensive dashboards, and the impact of dashboard usage on student outcomes. These themes strike at the core of the profession of teaching and showcase the importance of designing technology that aligns to the mission of the industry of which it serves. In this way, the current study serves to highlight the importance that professional identity expectancy has on willingness to adopt LA. Educators who feel that LA highly aligns to their personal vision of what it means to be a teacher are more likely to engage with LA. Prior studies have not addressed the role that professional identity expectancy has on technology adoption. The current study adds to the technology adoption and learning analytics corpus. This provides value to the research community. Involving faculty in LA design has benefits and challenges (Dollinger M. L., 2019). The concept of stakeholder buy-in has been shown as a critical factor in the success model that higher education institutions need in order to adopt LA at scale (Tsai, Kovanovic, & Gasevic, 2021). For profit companies that build and deploy LA tools are well served to understand the importance of faculty buy-in. And to the extent that such companies can create tools that mirror the mission and vision (specific characterizations of professional identity) of faculty, improved engagement and adoption of the tools are likely to follow. Stated slightly differently, future research and development into LA would be well served to ensure the tools are deemed to be easy to use, have high value and alignment to existing pedagogical practices, and fully embrace the alignment to professional identity. As it pertains to professional identity, LA marketing efforts could specifically capitalize on aligning LA to what it truly means to be a HE faculty. Instead of focusing on the mathematical underpinnings of LA, marketing could drive slogans such as “Becoming the best version of your teaching self through data informed course delivery”. In order to better foster LA adoption, HEI’s could benefit from explicitly demonstrating where LA aligns to the art and science of teaching. Hosting workshops that focus on specific teaching domains and clearly defined desired student experiences and outcomes would bring the conversation on LA directly to the professional life of the higher education faculty. In this way, the faculty member becomes one of the most critical stakeholders in the adoption model. Additionally, the data supports value HEI’s will find in highlighting where they are institutionally ready to implement LA. HEI’s would find value in internal marketing and information sharing on what specific database technologies, reporting systems, learning management support modules, and training is available. In this manner, higher education institutions can align with prior research on the dynamic factors that encompass business intelligence readiness (Hasan, Miskon, Ahmad, Syed, & Maarof, 2016). This research gives credence to the notion that efficacy is not as influential as the overall value proposition of LA adoption. As such, future research and development, as well as institutional adoption strategies, would be well served to focus on the “why” and less on the “what”. Leveraging the why in organizational behavior is a critical element of building institutional success (Sinek, 2011). Tying LA into what is means to be an educator and working to establish credence for LA being easy to use while serving to improve professional performance, will likely be an effective strategy in pushing higher education faculty towards LA adoption.

Limitations and Future Research

The theoretical model does show some weaknesses in places and the project does exhibit some limitations. The only respondents for the survey were higher education faculty at particular types of institutions within the United States. No international responses were recorded. There could exist a United States cultural bias towards professional identity expectations that limits the universality of the model. This particular study is a quantitatively based study that focuses on factors that influence learning analytics adoption. The results are only as a good as the instrument itself and the manner in which the respondents completed the survey. While much of the survey instrument relies on prior research items, some of the items were author created. These items have not been used multiple times across multiple projects. This weakness can be seen with some of the cross loading issues presented in the EFA data. The overall design of the survey can likely be improved in small places in an effort to ensure the proper question is being asked and answered. For example, the adverb "better" could be removed from statements focusing on professional identity. The statement *"Using learning analytics would help me to better realize my vision of what it means to be a higher education faculty member."* implies a focus on bettering or improving. The true intent of the construct is more binary in nature. The core investigation is on how one's professional identity plays a role in learning analytics adoption behavior. As such, a simple removal of the word better, along with changing to present tense, would improve this statement and help to ensure higher clarity for the survey respondent. The improved statement would read, *"Using learning analytics helps me realize my vision of what it means to be a higher education faculty member."* While the survey did provide a definition for LA, it is possible that survey respondents still did not have a clear vision in their minds of what LA are and how they might differ from traditional course analytics like class average on an exam. A cloudy vision of LA would impact the manner in which respondents completed the survey. Adding images of different learning analytics or even focusing the survey on one type of LA may provide clarity for the respondent and thereby resulting in more accurate data. Stronger and more reliable conclusions may then be drawn from such data. In the same vein of survey design and working to ensure responses are accurate, it is possible that survey respondents have either overstated or understated their true agreeance with different statements. As such, there may be inherent inaccuracies of responses. Future research can help to validate these findings. Only quantitative data was collected for this project. In the absence of additional supporting qualitative data, underlying factors that influence willingness to adopt LA may have gone undetected. The principal research target is the higher education faculty member. They are the primary stakeholder under investigation. Data collected through semi-structured interviews would add tremendous value to fully understanding the factors that influence or inhibit willingness to adopt learning analytics. A series of multiple case studies at different higher education institutions would also add value to the knowledge base and our understanding of learning analytics adoption. Prior research into professional identity and how identity may need to change has leveraged qualitative data (Reay, Goodrick, Waldorf, & Casebeer, 2017). In other places, LA usage and adoption research has also leveraged qualitative data (Dollinger M. L., 2019; Herodutou, Maguire, Hlosta, & Mulholland, 2023; Rienties, Herodotou, Olney, Schencks, & Boroowa, 2018). The current study does not presume a higher education faculty member's professional identity needs to change in order to adopt learning analytics. Nor does the study presume a HE faculty needs to have a professional identity that adheres to a specific set of characteristics. As such, it stands to reason that methodologies such as semi-structured interviews would help to reveal deeper insights into individual's true perception of their own professional identity. With this qualitative data in hand, research may uncover a deeper understanding of the relationship of specific professional identity themes to learning analytics adoption behavior. This research represents a point-in-time snap shot of learning analytics adoption behavior. Longitudinal studies may prove worthwhile as longitudinal studies aim to show trends over time. Adoption behaviors and influencers may morph from year to year. Additionally, there is value in continued work with the interaction role of perceived institutional LA readiness on willingness to adopt LA. The interplay between effort expectancy, performance expectancy, and professional identity expectancy is very strong. There is value in more research to disentangle these threads.

Conclusion

Technology continues to evolve and how human society interacts with and is influenced by technology also continues to evolve. As such, it becomes essential to periodically examine our understanding of influential factors that impact how an individual may or may not interact with a specific technology. The data supports the notion that foundational theoretical technology adoption models continue to provide a sound framework for understanding integration of new technologies, even when the technology is not a simple piece of hardware or individual piece of software. The data also supports that efficacy has varying impact on technology adoption and may be influenced by other stronger factors such as ease of use or professional identity expectancy. Understanding key challenges and opportunities of professional identity alignment, pedagogical alignment and perceptions of usability inform LA adoption strategies. Such strategies are necessary when working towards adopting LA on a large scale. The findings benefit the research community by continuing to evolve and mature the corpus of learning analytics research.

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Appendix A

IRB Application

DSU IRB APPLICATION FOR SURVEY RESEARCH

Email the electronic copy of this application and all associated documents to DSU IRB. Submitted materials must include CITI training dates for all investigators, and other institutional / organizational approval, all consent, recruitment and advertising materials for this project.

Project Title: Identifying Critical Factors That Impact Learning Analytics Adoption by Higher Education Faculty

Investigator Information

Please note: **A student's advisor is considered the "Principal Investigator" and has ultimate responsibility for the conduct of the student(s). CITI Training must be aligned with research.**

Principal Investigator: Dr.Jun Liu **School/Department:** College of Business and Information Systems **Email:** jun.liu@dsu.edu **Phone:** (605) 256-5172 CITI Date: Click or tap to enter a date.

Student or Co-Investigator: Michael Knupp **School/Department:** College of Business and Information Systems **Email:** michael.knupp@trojans.dsu.edy **Phone:** 207 404 5638 **CITI Date:** 6/10/2021

Co-Investigator: School/Department: Email: Phone: CITI Date: Click or tap to enter a date.

Co-Investigator: School/Department: Email: Phone: Click or tap here to enter text. CITI Date: Click or tap to enter a date.

Proposed Date of Project Implementation: 10/29/2021

Do any researchers listed have a potential conflict of interest associated with the research? (click here for definition)

☐ Yes: (contact the DSU IRB) ☒ No

Project Details

1. Is this study externally funded? (If yes, attach separate copy of funding summary and agency, or if tuition related, provide attachment noting agency and type of assistance)

   ☒ No ☐ Federal ☐ State ☐ Industry ☐ Federal-Tuition Related

2. If this project is for a student thesis or dissertation, has this research been approved by the dissertation / thesis committee?

   ☐ N/A ☒ Yes

   ☐ No. Do not submit an application until approval is granted.

3. Have you submitted, or do you plan to submit this study to another IRB?
   ☐ Yes: Please email the IRB approval letter and approved documents or provide date of upcoming review.
   ☒ No

4. Where will the research take place?
   ☐ In person ☒ Online Location of participants:

5. Have you attached letters of approval required from campus, facilities, schools or external organizations involved?
   ☐ Yes ☒ N/A

6. What is the purpose of your research? Fullfillment of PhD requirements

Procedures

7. Starting with initial recruitment contact with participants through close of project, describe the study procedures, listing all activities (include a copy of your study plan or protocol if developed, in your submission email): Please see the document titled "LearningAnalyticsAdoption_BriefPlanOfStudy.docx" that was included in the original IRB submission email.

8. How will you initially contact and select the participants (i.e. e-mail, flyer, social media post)? All recruitment materials must be submitted with your application. *Make sure the following federal requirements are included: the word "research," study purpose, estimated time commitment, eligibility criteria, and contact information for questions*. Email

9. How will you obtain the consent?
   ☒ Online before survey ☐ In the content of the email
   ☐ Mailed to the participant ☐ Verbal/Handout (face to face)
   ☐ Verbal (telephone)

10. Are you collecting signatures on the informed consent?
    ☐ Yes, hand-written ☐ Yes, electronic signature
    ☒ No, because my survey doesn't ask for any identifying information and I wish to keep participation anonymous

11. If this research will take place in a classroom, describe what non-participants will do during the research (activities and supervisions). Students not participating in the research should not be singled out or penalized. N/A

12. Will the participant(s) receive any compensation or extra credit? If so please describe what type (i.e. extra credit, gift card, monetary, other). *In addition, students must be told that they can withdraw from the study at any time without losing compensation/credit*. No

13. Please explain your alternative plan to obtain extra credit if a student chooses not to participate in the research. The alternative MUST be comparable to time spent participating in the research: N/A

Human participants

14. How many participants do you plan on enrolling? Ideally a target of 200 should suffice

15. Please describe the study populations by checking all that apply.
    ☒ Males ☒ Females
    ☐ University Students ☐ Students in Grades K-12
    ☐ Non-English Speaking

16. Are you specifically **targeting** an ethnic/international group? Check any that apply.
    ☐ African American ☐ Alaskan Native ☐ American Indian
    ☐ Asian ☐ Caucasian ☐ Hispanic
    ☐ Pacific Islander
    ☒ Other No specific ethnic/international group target

17. Age ranges of subjects to be enrolled?
    ☐ Birth-3 ☐ Preschool 3-5 ☐ Elementary 5-10
    ☐ Middle School 10-13 ☐ High School 14-17
    ☒ Adult 18-64 ☐ Senior Citizens 65 and up

18. Are any vulnerable populations listed below going to be enrolled in this study?
    ☐ Individuals with diminished mental/physical capacity
    ☐ Economically/educationally disadvantaged persons
    ☐ Your students ☐ Your employees
    ☐ Children ☐ Pregnant women
    ☐ Prisoners

19. Explain your inclusionary and exclusionary criteria and how participants will be screened (include locations in your answer). Inclusionary criteria for pilot study survey: full time faculty at Dakota State University, must have an active DSU email address. Inclusionary criteria for final survey: active teaching faculty member at a higher education university.

20. Are the proposed research participants your students or employees?
    ☒ No ☐ Yes.
    If yes, explain how you plan on avoiding your students feeling or perceiving undue influence for participation.

21. How do you have access to the study population? Yes - The proposed pilot study would be conducted with DSU faculty via an email distribution list. The final survey will be sent to higher education faculty. Specific faculty are being identified. Current possible pathways include the attendance list of a regional Business and IT conference (NABET),

membership list from a higher education professional organization, or a "pay for" service to obtain survey responses. Regardless of the mechanism, I feel I have access to the study population.

Risks and Benefits

22. Are there any of the following risks associated with the research? Please check all that apply.
    ☐ Economic Risk ☐ Psychological Risk
    ☐ Legal Risk ☐ Social Risk
    ☐ Collection of information reportable to authorities or collection of information that might render the subject prosecutable under the law (e.g. child abuse, alcohol abuse, danger to self or others.)

23. If you checked a box(es) in #22, describe the nature of each risk checked. The risks must be communicated to participants in the consent document &/or cover letter.

24. What direct and societal benefits do you expect the subject(s) you enroll to receive from this study? *If there is no direct benefit to the subjects, simply state that.* No direct benefit

Privacy and Confidentiality

25. Describe how the subject's privacy will be protected? *Privacy is about the person NOT the data. Please think about where the survey will be completed (i.e. in person or taken in private and browser closed when finished, etc.).* No personally identifiable data will be collected. Survey may completed at a private location as determined by the respondent. Survey will be completed online and closed at the end of the survey.

26. Does your survey ask for any identifying, or potentially identifying information?
    ☐ Yes; please list the identifying information (45 CFR 46.102(e)(5) see **Identifiable private information** for definition) and state why it's necessary to collect. Furthermore, please state how and when the data will be de-identified. Click or tap here to enter text.
    ☒ No

27. Elements of your data security plan (who will have access, storage location, encryption) :Survey Monkey will be the platform used to present and collect the survey responses. While Survey Monkey will collect the results, the resuts can only be accessed through a user id/password login process. Data that is downloaded from Survey Monkey will be stored locally on my computer which has two levels of authentication to access; BitLocker encryption password and an id/password authentication to access the Windows desktop.

28. You will keep a copy of the de-identified data for a minimum of three years, per federal law, including any additional requirements. ☒ I Agree ☐ I DO NOT Agree

Signatures

Electronically sign and email to the DSU IRB, contact us if you have questions.

By signing below:

- I attest that the information provided in this form is correct.
- I will not begin my research until I have received IRB approval.
- I will abide by the IRB requests to report on the status of the research.
- I will maintain records and documents according to regulatory, SD BoR, and university requirements.
- If funding is proposed for this research, I have notified Sponsored Programs.
- I agree to seek and obtain prior written approval from the IRB for any modifications to this research project, including changes in procedure, co-investigators, consent statements, survey/interview questions, etc.
- I will immediately report any unexpected or unanticipated problems or incidents that occur during the study.
- I will report in writing any significant findings which develop during the course of this research, which may affect the risks and benefits to the participants.

If the above conditions are not met, I understand that approval of this research may be suspended or terminated.

Principal Investigator: Jun Liu 6/16/2021
Signature
Date

Student Investigator: Michael Knupp 6/16/2021
Signature
Date

Co-Investigator: Click or tap to enter a date.
Signature
Date

Co-Investigator: Click or tap here to enter text. Click or tap to enter a date.
Signature
Date

By signing below, I attest that I reviewed the research plan and project materials described in this application and find the research scientifically and scholarly sound, and all requirements for approval have been met.

Chair/Director/Dean: Dorine Bennett 6/17/2021
Signature
Date

Advisor: Jun Liu 6/16/2021
(for Student Investigators) ***Signature*** ***Date***

Appendix B

IRB Approval Letter

Institutional Review Board
DAKOTA STATE UNIVERSITY
820 N. Washington Ave
Madison, SD 57042

Expedited Review Determination

Date: September 30, 2021
To: Jun Liu and Michael Knupp

Project Title: Identifying Critical Factors that Impact Learning Analytics Adoption by Higher Education Faculty
Approval #: 20210930

Dear Dr. Liu and Mr. Knupp:

The Dakota State University IRB has conducted expedited review, in accordance with federal requirements under 45 CFR 46.110, of your project and approved it on 9/30/21. This approval was based on your project's meeting the condition of: *Research that only includes no more than minimal risk to participants.*

To maintain its approved status, your research must be conducted according to the most recent plan reviewed by the IRB. You must notify the IRB in writing within four days of:

- Any changes to your research plan or departure from its description as stated in your application and/or other documents submitted;
- Any unexpected or adverse event that occurs in relation to your research project.

Within 364 days of the date of this letter, you must submit:

- A notice of closure once all project activities have concluded;
  -- or --
- An application for extension of time to complete your research.

If you have any questions regarding this determination or during the course of your study, please contact us at 605-256-5100 or irb@dsu.edu. Best wishes to you and your research.

Yours truly,

Jack H. Walters

Jack H. Walters, Chair

Appendix C

Distributed Survey

Learning Analytics Adoption - Final National Survey

Verification of Responder Qualification

Thank you for participating in our survey. Your feedback is important.

* 1. What is your primary role in the education industry?

Note - If you do not qualify for this survey, the survey will automatically close.

- ◯ Elementary School Teacher
- ◯ High School Teacher
- ◯ Full Time Higher Education Faculty (at an institution that awards 2 year, 4year and/or doctoral degrees)
- ◯ Administration (Principal, Dean, etc.)

Learning Analytics Adoption - Final National Survey

Consent Statement

You are invited to participate in a research study regarding your adoption of learning analytics into your pedagogical practice. I (Michael Knupp) am a PhD candidate within the College of Business and Information Systems at Dakota State University, and am conducting this survey as part of my dissertation research project. In order to participate, you must be a full-time faculty member at an institute of higher learning that awards associate's, bachelor's, master's, or doctoral degrees.

The purpose of this study is to explore critical factors which influence the adoption of learning analytics by higher education faculty. Also of interest is how higher education faculty perceive the data driven decision support culture.

We believe there are no risks involved in participating in this survey. No personally identifiable data is being collected that could be used to match responses with individual faculty members. You will not be compensated for your participation in this survey.

The records of this study will be kept confidential to the extent permitted by law. To protect your privacy, we will not include any information that could identify you. Please note that we are unable to ensure the security of the computer on which you choose to enter your responses and urge you to maintain security and privacy in your choice of computers to complete the survey.

Participating in this study is voluntary. If you decide to be part of the study, you may change your mind and stop at any time. You do not have to answer any questions you do not want to answer.

If you have questions, please contact Michael Knupp at 207 404 5638. Additional inquiries can also be made to Dr. Jun Liu of Dakota State University at 605 256 5172. If you have any questions about your rights as a human subject, complaints, concerns, or wish to talk to someone who is independent of this research, contact the Dakota State Institutional Review Board staff at 605-256-5100. Thank you for your time.

Your consent to participate is assumed if you answer any of the questions below. The survey should take approximately 5 - 8 minutes to complete.

Learning Analytics Adoption - Final National Survey

Definition of Learning Analytics

The purpose of the study is to explore critical factors which influence the adoption of learning analytics by higher education faculty. Also of interest is how higher education faculty perceive the data driven decision support culture.

The 2011 inaugural Learning Analytics and Knowledge conference defined learning analytics as the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and environments of which it occurs.

Learning analytics can include, but are not limited to, descriptive statistics of class grade distributions, analytics as provided within a learning management system, dashboards of student performance, metrics and graphs of course content utilization and network analyses of online discussion boards.

Broadly speaking, learning analytics include any metrics or graphical representations of data collected on learners that higher education faculty can leverage to better understand and improve the learner experience.

Learning Analytics Adoption - Final National Survey

Learning Analytics Tools and Technology

* 2. Indicate your level of confidence with the following activities.

	Not At All Confident	Slightly Confident	Somewhat Confident	Fairly Confident	Completely Confident
Identifying the appropriate learning analytics needed to assess individual student performance.					
Identifying the appropriate learning analytics needed to assess group level performance.					
Using learning analytics tools to retrieve charts, tables or graphs for analysis.					
Using learning analytics tools to filter students into different groups for analysis.					
Using learning analytics tools to access student performance reports.					
Describing learning analytics information presented in column charts, bar chart or pie charts.					
Describing learning analytics information presented in radar charts, heat maps or social network graphs.					
Determining actionable insight from learning analytics.					

Learning Analytics Adoption - Final National Survey

Data Cycle

* 3. Indicate your level of confidence with the following activities.

	Not At All Confident	Slightly confident	Somewhat Confident	Fairly Confident	Completely Confident
Explaining the data cycle model.	○	○	○	○	○
Describing how the data cycle model provides a foundation for learning analytics technologies.	○	○	○	○	○
Correlating different phases of the data cycle model to your usage of learning analytics.	○	○	○	○	○
Explaining how the data cycle process flow is reflected in the art of teaching.	○	○	○	○	○

Learning Analytics Adoption - Final National Survey

Learning Analytics Effort Expectancy

* 4. To what extent do you agree with the following statements?

	Strongly Disagree	Disagree	Equally Disagree / Agree	Agree	Strongly Agree
My interaction with learning analytics would be clear and understandable.	○	○	○	○	○
It would be easy for me to become skillful at using learning analytics.	○	○	○	○	○
I would find learning analytics easy to use.	○	○	○	○	○
Understanding how to use learning analytics is easy for me.	○	○	○	○	○

Learning Analytics Adoption - Final National Survey

Performance Expectations

* 5. To what extent do you agree that **using learning analytics** would ...

	Strongly Disagree	Disagree	Equally Disagree / Agree	Agree	Strongly Agree
Enable you to accomplish your pedagogical tasks more quickly.	○	○	○	○	○
Improve your pedagogical performance.	○	○	○	○	○
Increase your productivity.	○	○	○	○	○
Enhance your pedagogical effectiveness.	○	○	○	○	○
Make it easier to do your job.	○	○	○	○	○
Increase the quality of output in your job.	○	○	○	○	○

Learning Analytics Adoption - Final National Survey

Learning Analytics and Professional Identity

* 6. To what extent do you agree with the following statements?

	Strongly Disagree	Disagree	Equally Disagree / Agree	Agree	Strongly Agree
Incorporating learning analytics into my teaching practice would make me feel closer to the professional community of higher education faculty members.	○	○	○	○	○
I could better achieve my professional goals by using learning analytics in my practice.	○	○	○	○	○
Using learning analytics would help me to better realize my vision of what it means to be a higher education faculty member.	○	○	○	○	○
I believe the purpose of learning analytics reflect my version of the core ideals of being a higher education faculty member.	○	○	○	○	○

Learning Analytics Adoption - Final National Survey

Learning Analytics Institutional Readiness

* 7. As it pertains to how you perceive your place of employment, indicate your agreement of the following.

	Strongly Disagree	Disagree	Equally Disagree / Agree	Agree	Strongly Agree
Possesses the technical infrastructure (databases, networks, applications, etc.) required to implement learning analytics technology.	○	○	○	○	○
Has executive sponsorship that promotes data informed decision making.	○	○	○	○	○
Recognizes individuals that incorporate data into various decision making processes.	○	○	○	○	○
Provides enough training for me to find and access learning analytics.	○	○	○	○	○
Offers professional development opportunities to advance my knowledge and skills required to use learning analytics.	○	○	○	○	○

Learning Analytics Adoption - Final National Survey

Intention to Use Learning Analytics

* 8. For the following statements, indicate your level of usage frequency.

	Strongly Disgree	Disagree	Agree	Strongly Agree
I hope to use learning analytics in the coming academic year.	◯	◯	◯	◯
I intend to use learning analytics in the coming academic year.	◯	◯	◯	◯
I hope to use learning analytics in the next 2-5 years.	◯	◯	◯	◯
I intend to use learning analytics in the next 2-5 years.	◯	◯	◯	◯

Learning Analytics Adoption - Final National Survey

Current Usage and Technology Adoption Behavior

* 9. Do you currently use learning analytics in your professional practice?

◯ No

◯ Yes

* 10. Do you tend to use traditional external review information, such as student feedback surveys, to improve your professional practice?

◯ No

◯ Yes

◯ My university does not utilize student feedback surveys.

* 11. How do you self-identify your technology adoption behavior?

◯ Laggard (very skeptical of change, resistance to adoption, hold on to traditional methods)

◯ Late Majority (skeptical of change, require majority to adopt first)

◯ Early Majority (embrace change ahead of average person, require some evidence before change)

◯ Early Adopter (embrace and lead change, comfortable with new ideas)

◯ Innovator (first to adopt, venturesome, risk taker)

Learning Analytics Adoption - Final National Survey

Teaching Demographic Information

* 12. How many years have you been teaching in higher education?

* 13. What is your primary teaching discipline?

- Business (Accounting, Finance, Business Management, etc.)
- Humanities (English, History, Art, Mathematics, etc.)
- Natural Sciences (Biology, Chemistry, Physics, Ecology, etc.)
- Social Sciences (Psychology, Sociology, etc.)
- Information Technology (Programming, IT infrastructure, IT Security, etc.)
- Data Science (Analytics, Data Visualization, Machine Learning, etc.)
- Other

* 14. What is the approximate percentage of in-person, online or hybrid classes that you teach? (Enter whole numbers that must total 100.)

Important Definitions
In-person Class = traditional face-to-face delivery in a classroom
Online Class = delivered exclusively online
Hybrid Class = partially delivered in-person and partially online

In-person Classes

Online Classes

Hybrid Classes

Learning Analytics Adoption - Final National Survey

Survey Conclusion

This concludes the survey. Thank you for your participation.